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LUANA LAVAGNOLI MOREIRA

VERIFICATION OF EFFICACY OF FLOOD VULNERABILITY INDICES THROUGH SENSITIVITY ANALYSIS

PORTO ALEGRE

2022

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Dissertation present to the Gradutaion Program on Water Resources and Environmental Sanitation of Federal University of Rio Grande do Sul, as a partial requirement to obtain the doctor's degree.

Advisor: Prof. Dr. Masato Kobiyama
Co-Advisor: Prof. Dr. Diogo Costa Buarque

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Little drops of joy!

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Resumo

Título: VERIFICAÇÃO DA EFICÁCIA DE ÍNDICES DE VULNERABILIDADE A INUNDAÇÕES ATRAVÉS DE ANÁLISES DE SENSIBILIDADE

Os índices e indicadores são amplamente usados para mensurar a vulnerabilidade a inundações, uma vez que a vulnerabilidade é uma grandeza multidimensional englobando aspectos sociais, econômicos, ambientais, culturais e físicos. No entanto, a construção desses índices carregam incertezas que são raramente consideradas. Assim, o principal objetivo desta tese é verificar a a sensibilidade de índices de vulnerabilidade a inundações por meio da mudança de parâmetros de entrada. Para isso, realizou-se (1) uma busca de deficiências nos estudos de índices de vulnerabilidade; (2) verificou-se o efeito da utilização de diferentes métodos de normalização, agregação e classificação dos índices de vulnerabilidade a inundações; e (3) foram avaliadas a sensibilidade e as incertezas envolvidas na atribuição de pesos aos indicadores de vulnerabilidade. Os estudos foram desenvolvidos na bacia do rio Maquiné, localizada na região nordeste do estado do Rio Grande do Sul (Brasil), região serrana onde os eventos de inundação são frequentes e afetam a população todos os anos. Dos 95 artigos analisados, encontramos lacunas relacionadas à falta de análise de sensibilidade e incerteza na escolha de métodos normalização, ponderação e agregação (presentes em apenas 9,5% dos artigos), validação inadequada ou inexistente dos resultados (presente em 13,7% dos estudos), falta de transparência quanto à fundamentação da ponderação e seleção de indicadores, e uso de abordagens estáticas, desconsiderando a dinâmica temporal. A escolha de diferentes métodos de normalização resulta em baixa sensibilidade. Por outro lado, na análise do método de agregação dos indicadores, observou-se que a escolha do método geométrico produziu diferenças substanciais na vulnerabilidade espacial e tendeu a subestimá-la. Além disso, a classificação da vulnerabilidade levou a resultados excessivamente sensíveis. Quando exploramos as mudanças na vulnerabilidade a inundações usando ponderação igual e aplicando pesos derivados de dados de pesquisa participativa, foi observado pouco efeito nos resultados de vulnerabilidade. Além disso, a preferência dos pesos dos indicadores não diferiu significativamente entre as distintas características socioeconômicas dos participantes. Os resultados obtidos podem apoiar os tomadores de decisão na redução da incerteza e no aumento da qualidade das avaliações de vulnerabilidade a inundações.

Palavras-chave: Índice. Indicador. Inundações. Vulnerabilidade.

Abstract

Indices and indicators are widely used to measure flood vulnerability since vulnerability is a multidimensional, covering social, economic, environmental, cultural and physical aspects. However, the index construction carries uncertainys that are rarely considered. Thus, the main goal of this thesis is to verify the sensitivity of flood vulnerability indices through changes in the input parameters. To achieve this, we (1) found the gaps on vulnerability index studies; (2) verified the effect of using different methods of normalization, aggregation, and classification of flood vulnerability indices; and (3) assessed sensitivity and uncertainties involved in assigning weights to flood vulnerability indicators. The studies were developed in the Maquiné river basin, located in the northeastern region of the state of Rio Grande do Sul (Brazil), a mountainous region where flood events are frequent and affect the population every year. From 95 articles, we found gaps related to lack of sensitivity and uncertainty analyses (present in only 9.5% and 3.2% of papers, respectively), inadequate or inexistent validation of the results (present in 13.7% of the studies), lack of transparency regarding the rationale for weighting and indicator selection, and use of static approaches, disregarding temporal dynamics. The analysis by using different normalization indicators methods results in low sensitivity. Conversely, when analysing the indicators' aggregation method, it was observed that the adoption of the geometric method produced substantial differences on the spatial vulnerability and tended to underestimate the vulnerability. Additionally, the vulnerability classification into different classes led to overly sensitive outputs. When we explored changes in vulnerability scores using equal weighting and by applying weights derived from participatory survey data, little effect on flood vulnerability results was observed. Besides, the preference of the indicators’ weights did not significantly differ among distinct socioeconomic characteristics of stakeholders. The obtained results can give support to decision-makers in reducing uncertainty and increasing the quality of flood vulnerability assessments.

Keywords: Index. Indicator. Flood. Vulnerability.

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List of Abbreviations and acronyms

AHP	Analytic Hierarchy Process
AIC	Akaike's information criterion
ANP	Analytic Network Process
BBN	Bayesian Belief Networks
CEPED-UFSC	*Centro de Estudos e Pesquisas em Engenharia e Defesa Civil – Universidade Federal de Santa Catarina*
CRED	Centre for Research on the Epidemiology of Disasters
DEA	Data Envelopment Analysis
EM-DAT	Emergency Events Database
GDP	Gross Domestic Product
GIS	Geographic Information System
IBGE	*Instituto Brasileiro de Geografia e Estatística*
IPCC	Intergovernmental Panel on Climate Change
MCDM	Multiple-criteria decision-making
MOVE	Method for the Improvement of Vulnerability Assessment
NHESS	Natural Hazards and Earth System Sciences
OEP-EOP	Office of Emergency Preparedness of the Executive Office of the President of the United States
PCA	Principal Components Analysis
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
SA	Sensitivity Analysis
SPSS	Statistical Package for the Social Sciences
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
UNEP	United Nations Environment Programme
UNISDR	United Nations International Strategy for Disaster Reduction
WoS	Web of Science

List of Symbols

AG	Geometric aggregation
AL	Linear aggregation
CB	Census Blocks
G_k	k^{th} class of data
m	Number of classes
n_k	Number of data in class G_k
$N1$	Min-max normalization method
$N2$	Z-scores normalization method
$N3$	Distance to target normalization method
$N4$	Ranking normalization method
P^i	The i-th percentile of the distribution of the indicator x_{in}
w_{in}	Weight of indicator *in*
X	Global sum of x_i data
x_i	Geospatial data (index value)
x_{in}	Indicator variable *in*
$\bar{x}_{in}$	Average of indicator *in*
y_{in}	Transformed variable of x for indicator
$\sigma_{\bar{x}_{in}}$	Standard deviation of indicator *in*

Contents

CHAPTER 1

Introduction

1.1. Background

Flood is the most frequent hydrological disaster globally (CRED, 2020). According to the Emergency Events Database (EM-DAT) in the last 10 years (2009-2019) there were about 50,000 deaths worldwide due to flooding, and an average of 1% of the world population was affected. In Brazil, floods are responsible for 72% of the deaths caused by disasters. Of the people affected by disasters in Brazil, about 33% have suffered from flooding (CEPED - UFSC, 2013).

The increase in the number of disasters associated with floods is a consequence of several factors, such as population growth, change in land use, land-use planning, and climate change (IPCC, 2007). Thus, it is necessary to manage the risk of flooding for control and mitigation purposes, being an ally in decision-making by water resources managers.

Vulnerability is essential in flood risk assessment, as hazards only turn into disasters if there are vulnerable people or infrastructure located in areas exposed to hazards (KOBIYAMA; GOERL; MONTEIRO, 2018). Thus, knowledge of vulnerability is essential to assess the susceptibility of elements exposed to risk (KARAGIORGOS *et al.*, 2016), considering multiple social, economic, physical, cultural, environmental, and institutional dimensions (BIRKMANN *et al.*, 2013).

According to Nasiri, Yusof, and Ali *et al.* (2016), the main methods for assessing vulnerability to flooding are: (i) vulnerability curve, (ii) disaster loss data, (iii) computer modeling and (iv) based in indices. The latter is recommended by several authors for allowing a holistic analysis of the dimensions of vulnerability, aiming to ensure a better representation of reality (BALICA *et al.*, 2013; BIRKMANN *et al.*, 2013; FUCHS; KUHLICKE; MEYER, 2011; NASIRI; MOHD YUSOF; MOHAMMAD ALI, 2016). Furthermore, it helps simplify the system's conditions and behaviour, summarize complex and multidimensional issues, facilitate interpretations by end-users, and reduce the number of indicators (SAISANA; TARANTOLA, 2002).

Despite the advantages of using indices, there are some limitations, as each stage of index construction carries uncertainties (JORGENSEN; BURKHARD; MÜLLER, 2013; NAZEER; BORK, 2019). These uncertainties are mainly related to the choice of indicators, the normalization stage, the assignment of weights, the aggregation methods (CHEN, H. *et al.*, 2011; CROSETTO; TARANTOLA; SALTELLI, 2000; LIGMANN-ZIELINSKA; JANKOWSKI, 2014; MALCZEWSKI, 2006), and in the index classification stage (MOREIRA *et al.* 2021a). The methodological choices made during the construction of the index imply assumptions, subjectivity, and uncertainties that must be identified and recognized (BALICA; WRIGHT, 2010; NARDO *et al.*, 2008).

In the last 5 years, in Brazil and worldwide, there has been an increase in the use of indices to assess vulnerability to flooding. However, of the studies aimed at the use of vulnerability index to floods, most do not perform sensitivity analyzes (90.5%), uncertainties (96.8%), or validation (86.3%), which demonstrates limited reliability of these indices (MOREIRA *et al.* 2021b). In the Brazilian context, the reality is more worrying, considering that only Debortoli *et al.* (2017) and de Brito; Evers; Almoradie (2018) validated the results, and none assessed sensitivity and uncertainties in studies of vulnerability indices to flooding (MOREIRA; KOBIYAMA, 2021).

Given the aforementioned limitations, this study aims to understand the sensitivity of flood vulnerability indices, considering different normalization methods, weight assignments, aggregation, and classification techniques. It is hypothesized that the changes at each stage in the construction and classification of the flood vulnerability index significantly change the results and induce the erroneous actions of managers to control and mitigate flood disasters.

1.2. The theoretical foundation of flood vulnerability

To understand the processes involved in flood risk and vulnerability analysis, it is first necessary to understand the concepts of risk, its components, and their relationship. There are a variety of concepts in the literature involving the terms risk, hazard, vulnerability, coping capacity, adaptive capacity, resilience, susceptibility, sensitivity, and exposure. There is no clear relationship between them and some have different meanings when used in different contexts (BROOKS, 2003).

Risk estimation originated in the field of statistics (LUHMANN, 1991), although it is currently used in several areas of knowledge. When it comes to natural disasters, the concept of risk considers two approaches:

i) probability of occurrence of the hazard and its consequences related to losses;
ii) the relationship between the terms danger, exposure, sensitivity, vulnerability, and adaptability.

Hazard refers to the probability of occurrence of an event with a certain intensity in a specific location during a certain period of exposure (CARDONA, 2003), it is a natural process or phenomenon that can constitute a harmful event that can cause loss of life, health impacts, property damage, social and economic disturbances or environmental degradation (UNISDR, 2016).

Flooding is a hazard usually represented in the form of maps that show flooding characteristics, such as height, area, and duration of the flood, flow velocity, among others. These variables are obtained through hydrological and hydrodynamic models that also allow evaluating the peak flow and flood propagation in time and space (SAMPSON *et al.*, 2015).

Among the terms that make up risk, vulnerability tends to be a fuzzy one as it does not yet have a consolidated and universally accepted definition. The study of vulnerability emerged between the 1950s and 1960s in the area of behavioral sciences (CUTTER; EMRICH, 2006); but the use of the term vulnerability in the context of natural disasters emerged in 1972, presented by the Office of Emergency Preparedness of the Executive Office of the President of the United States, as the predisposition of people, communities or large jurisdictions and sectors of the economy, agriculture and infrastructure to be affected by natural disasters (OEP-EOP, 1972).

Over the decades, the concept of vulnerability has constantly changed. As can be seen in Table 1-1, the different notions of this concept can be listed in the following aspects (VILLAGRÁN DE LEÓN, 2006):

i) a particular condition of a system before a disaster occurs, related to criteria such as susceptibility, limitations, disabilities, or deficiencies;
ii) a direct consequence of exposure to a certain hazard;

iii) probability resulting from a system when exposed to an external event associated with a hazard, expressed in terms of potential losses such as fatalities or economic losses.

Table 1-1 – Overview of vulnerability concepts adopted through the years.

Concept	**Reference**
The predisposition of people, communities, or larger jurisdictions, and of sectors such as economy, agriculture, and infrastructure to be affected by a natural disaster	OEP-EOP (1972)
Is the threat (to hazard materials) to which people are exposed (including chemical agents and the ecological situation of the communities and their level of emergency preparedness)	Gabor; Griffith (1980)
Is the degree to which a system or part of a system may react adversely to the occurrence of a hazardous event. The degree and quality of that adverse reaction are partly conditioned by the system's	Timmerman (1981)
Is the degree to which different classes of society are differentially at risk, both in terms of the probability of occurrence of an extreme physical event and the degree to which the community absorbs the effects of the extreme physical event and helps different classes to recover	Susman; O'Keefe (1984)
Is the threat or interaction between risk and preparedness. It is the degree to which hazardous materials threaten a particular population (risk) and the capacity of the community to reduce the risk or adverse consequences of hazardous materials releases	Pijawka; Foote; Soesilo (1985)
Capacity to suffer harm and react adversely, how the society responds to the perturbation	Kates (1985)
Is operationally defined as the inability to take effective measures to insure against losses. When applied to individuals, vulnerability is a consequence of the impossibility or improbability of effective mitigation and is a function of our ability to detect the hazard	Bogard (1988)
The exposure to contingencies and stress, and difficulty coping with them. The vulnerability has thus two sides: an external side of risks, shocks, and stress to which an individual or household is subject; and an internal side which is defenselessness, meaning a lack of means to cope without damaging loss	Chambers (1989)
Is the potential for loss	Mitchell (1989)
Has been related or equated to concepts such as resilience, marginality, susceptibility, adaptability, fragility, and risk	Liverman (1990)
Has three connotations: it refers to a consequence rather than a cause; it implies an adverse consequence; and it is a relative term that differentiates among socio-economic groups or regions, rather than an absolute measure of deprivation	Downing (1991)
Is the differential capacity of groups and individuals to deal with hazards, based on their positions within physical and social worlds	Dow (1992)
Human vulnerability is a function of the costs and benefits of inhabiting areas at risk from natural disaster	Alexander (1993)
Is the likelihood that an individual or group will be exposed to and adversely affected by a hazard. It is the interaction of the hazards of place (risk and mitigation) with the social profile of communities	Cutter (1993)

Table 1-1 – Overview of vulnerability concepts adopted through the years.

Concept	**Reference**
Is defined in terms of exposure, capacity, and potentiality. Accordingly, the prescriptive and normative response to vulnerability is to reduce exposure, enhance coping capacity, strengthen recovery potential and bolster damage control via private and public means	Watts; Bohle (1993)
The measure of human welfare integrating social, economic, and political exposure to a range of harmful perturbations	Bohle; Downing; Michael (1994)
Factors that magnify or attenuate the effects of an extremely natural, technological, or human-induced event and those factors that decrease a community or individual's ability to rebound after the event has occurred	Tobin; Montz (1997)
The function of two attributes: exposure (the risk of experiencing a hazardous event); and coping ability, subdivided into resistance (the ability to absorb impacts and continue functioning), and resilience (the ability to recover from losses after an impact).	Clark *et al.* (1998)
Exposure of groups or individuals to stresses both from exogenous risks, in this case from climate change, and from their social and economic situation	Adger (1996)
Circumstances that place people at risk while reducing their means of response or denying them available protection	Comfort *et al.* (1999)
The potential for casualty, destruction, damage, disruption, or other forms of loss concerning a particular element	Alexander (2000)
Ability or inability of individuals and social groupings to respond to, in the sense of coping with, recover from, or adapt to, any external stress? placed on their livelihoods and well-being	Kelly; Adger (2000)
The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity	IPCC (2001)
Two components: "the insecurity and defenselessness experimented by communities, families, and individuals in their livelihoods as a consequence of the impact of a socio-economic event of traumatic character; and the second component is the management of resources and strategies which are utilized by these communities, families, and individuals to cope with the effects of this event	Pizarro (2001)
The propensity of an endangered element due to any kind of natural hazard to suffer different degrees of loss or amount of damage depending on its particular social, economic, cultural, and political weaknesses	Alcántara-Ayala (2002)
The degree to which an exposure unit is susceptible to harm due to exposure, to a perturbation or stress, in conjunction with its ability (or lack thereof) to cope, recover or fundamentally adapt (become a new system or become extinct)	Kasperson *et al.* (2002)
Human vulnerability can be defined as the exposure to hazard by external activity together with the coping capacity of the people to reduce the risk from the exposure. Vulnerability is also connected with access to opportunities, which defines the ability of people to deal with the impact of the hazard to which they are exposed. It means the characteristics of a person or a group of people in terms of their capacity to anticipate, cope with, resist, and recover from the impact of the risk or hazard.	UNEP (2003)

Table 1-1 – Overview of vulnerability concepts adopted through the years.

Concept	**Reference**
An internal risk factor of the subject or system that is exposed to a hazard and corresponds to its intrinsic predisposition to be affected, or to be susceptible to damage. Represents the physical, economic, political, or social susceptibility or predisposition of a community to damage in the case of a destabilizing phenomenon of natural or anthropogenic origin	Cardona (2003)
Vulnerability is broken down into three components: exposure (location relative to hazard, environmental surrounding), resistance (livelihood, health), and resilience (adjustments, preparation)	Pelling (2003)
The degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stressor	Turner *et al.* (2003)
Characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard	Wisner *et al.* (2003)
Relating something or someone vulnerable to something else as a source of potential harm because of some property of the subject or the object	Green (2004)
State of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt	Adger (2006)
The residue of potential damages which cannot be targeted through the implementation of typical measures; or as conditions of incapacity to cope with disasters once they have taken place	Villagran De Leon (2006)
Considered as the extent of harm, which can be expected under certain conditions of exposure, susceptibility, and resilience. By combining all the above-mentioned definitions, the general vulnerability concept can be expressed as Vulnerability = Exposure + Susceptibility - Resilience	Balica; Douben; Wright (2009)
Conditions are determined by physical, social, economic, and environmental factors or processes which increase the susceptibility of an individual, a community, assets, or systems to the impacts of hazards.	UNISDR (2016)
Social, economic, physical, environmental, institutional, and cultural conditions in terms of fragility and abilities to cope before, during, and after a dangerous event	Present study

In terms of components, some authors consider vulnerability as a function of exposure and susceptibility (BALICA, S. F.; DOUBEN; WRIGHT, 2009; IPCC, 2001; TURNER *et al.*, 2003; UNISDR, 2016). Other authors separate the term exposure from vulnerability (DILLEY *et al.*, 2005; FEDESKI; GWILLIAM, 2007) since it is possible to be exposed to danger and not be vulnerable. For example, a person may live in an area at risk of flooding, but is able to modify their housing and avoid potential damage.

Exposure can be defined as a situation that people, infrastructure, housing, productive capacities, and other human resources are located in areas prone to hazards (UNISDR, 2016), which includes, for example, people, housing, property, economic activities, physical infrastructure, and environmental resources. While susceptibility represents the probability of elements at risk (people and resources) to suffer harm (UNDP, 2014).

Two similar components of vulnerability are coping capacity, related to the ability of people, organizations and systems, using available resources and skills, to deal with and manage adverse conditions, emergencies, or disasters (UNISDR, 2016; VILLAGRÁN DE LEÓN, 2006) and adaptive capacity, which refers to the strategies that allow communities to promote changes to deal with negative consequences resulting from natural disasters (WELLE; BIRKMANN, 2015). The first term is associated with short-term guidelines and the second with long-term perspectives, most used in the context of climate change (CARDONA *et al.*, 2012).

Similarly, the term resilience can be seen as the ability of a system, community, or society, exposed to danger, to resist, absorb, accommodate, adapt, transform and recover from the effects of a hazard within a period, including preservation and restoration of their basic structures and functions through risk management (UNISDR, 2016). Some authors consider this term part of vulnerability, while others treat it separately but with concepts linked to one another (CUTTER *et al.*, 2008).

1.3. Indices and indicators

Indices and indicators have been used for a long time. In the 1920s, indices were considered to measure changes in quantitative data that could not be directly observed (BOWLEY, 1920). Although they cannot measure something, they could indicate its quantitative variations (KEYNES, 1920). In the 40s, economic indicators emerged, and in the 1960s and 1970s social indicators were developed, while environmental indicators emerged in the 1970s with the establishment of environmental policies (BIRKMANN, 2006).

There are several definitions of indices and indicators in the scientific literature, many ambiguous and contradictory concepts given their generalization (BIRKMANN, 2006). There is a general yet comprehensive definition created by Saisana and Tarantola (2002) where the indicators result in several pieces of data capable of synthesizing the characteristics of a system, and the aggregation of these indicators through a mathematical combination is called an index or composite indicator.

Indices serve as a summary of complex, multidimensional issues intended to assist decision-makers; facilitate the interpretation of a phenomenon; arouse the public's interest through a summary figure of the results; help reduce the number of bookmarks, and can include more information in a limited space.

However, it is worth highlighting some limitations since the indices can present misleading messages if they are poorly constructed or misinterpreted, and the use of sensitivity analysis is recommended to ensure their robustness. The steps of construction of the index involve the judgment of people to choose the indicators, models, weight of the indicators, etc., these judgments must be transparent (SAISANA; TARANTOLA, 2002).

A good index must meet the following criteria (BIRKMANN, 2006; NARDO *et al.*, 2008):

- relevance - statistically meets the current and potential needs of users;
- accuracy - estimate close to true values;
- punctuality - the period between the availability of information and the phenomenon to be measured;
- accessibility - physical conditions under which users can access data;
- interpretability - easy to understand to analyze the data;
- coherence - the degree to which data is logically connected and consistent;
- reproducibility – applicability in other studies;
- based on available data – facilitates reproducibility;
- comparable;
- measurable;
- cost-benefit.

Therefore, given the importance of holistic studies on vulnerability to ensure a better representation of reality, vulnerability indices are recommended (BALICA *et al.*, 2013; BIRKMANN *et al.*, 2013; FUCHS *et al.*, 2011; NASIRI *et al.*, 2016).

1.4. Goals

The principal objective of this research is to verify the sensitivity of flood vulnerability indices through changes in the input parameters. To achieve this objective, the following specific objectives are sought:

- Goal 1: Identify the gaps on present a state-of-the-art study on vulnerability index studies in the world through a bibliographic review;

- Goal 2: Check the effect of using different methods of normalization, aggregation, and classification of flood vulnerability indices;
- Goal 3: Assess the level of sensitivity and uncertainties involved in assigning weights to flood vulnerability indicators.

1.5. Structure of the dissertation

This dissertation is organized into five chapters, as shown in Figure 1-1.

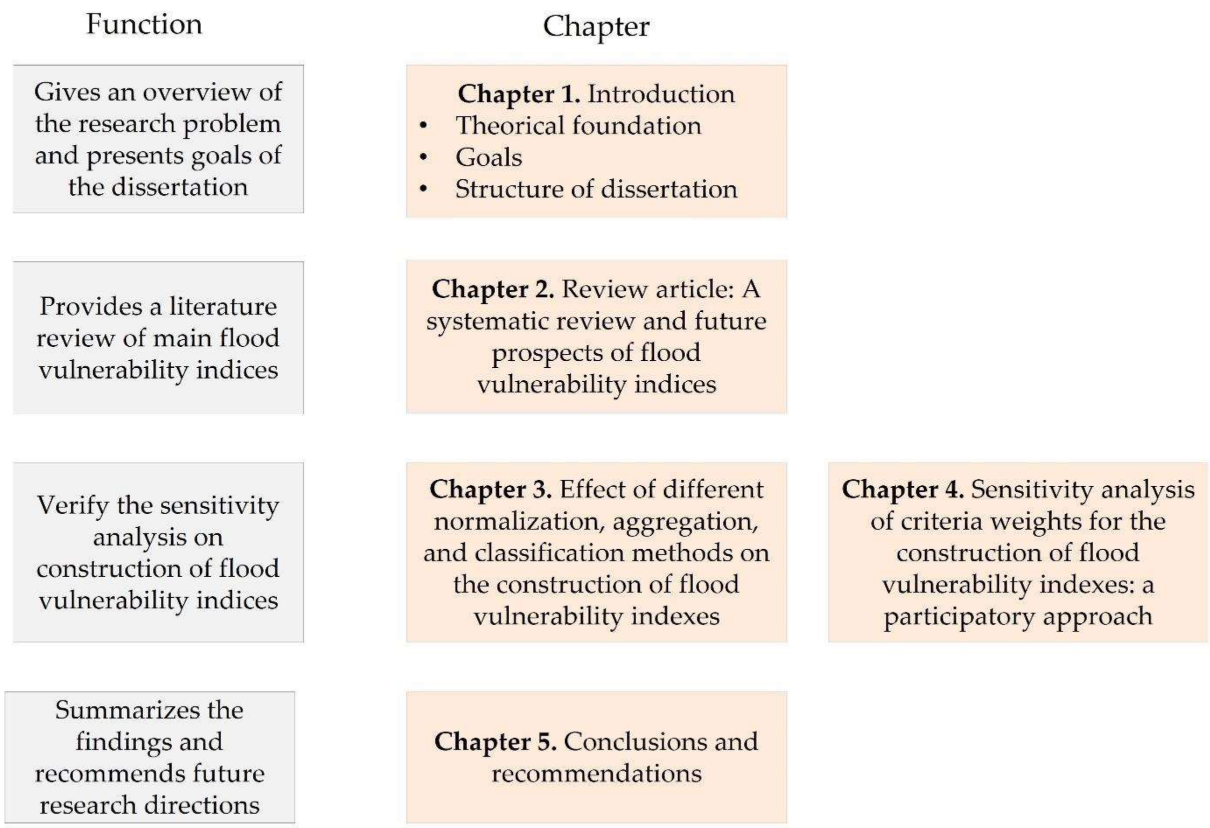

Figure 1-1 - Overview of the chapters of the dissertation.

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CHAPTER 2

Review article: A systematic review and future prospects of flood vulnerability indices

This chapter is based on the following paper published in Natural Hazards and Earth System Sciences (NHESS):

MOREIRA, L.L.; de BRITO, M.M.; KOBIYAMA, M. Review article: A systematic review and future prospects of flood vulnerability indices. NHESS, v. 21, n. 5, p. 1513-1530, 2021.

Abstract. Despite the increasing body of research on flood vulnerability, a review of the methods used in the construction of vulnerability indices is still missing. Here, we address this gap by providing a state-of-art account on flood vulnerability indices, highlighting worldwide trends and future research directions. A total of 95 peer-reviewed articles published between 2002–2019 were systematically analyzed. An exponential rise in research effort is demonstrated, with 80% of the articles being published since 2015. The majority of these studies (62.1%) focused on the neighborhood followed by the city scale (14.7%). Min–max normalization (30.5 %), equal weighting (24.2%), and linear aggregation (80.0%) were the most common methods. With regard to the indicators used, a focus was given to socioeconomic aspects (e.g., population density, illiteracy rate, and gender), whilst components associated with the citizen's coping and adaptive capacity were slightly covered. Gaps in current research include a lack of sensitivity and uncertainty analyses (present in only 9.5% and 3.2% of papers, respectively), inadequate or inexistent validation of the results (present in 13.7% of the studies), lack of transparency regarding the rationale for weighting and indicator selection, and use of static approaches, disregarding temporal dynamics. We discuss the challenges associated with these findings for the assessment of flood vulnerability and provide a research agenda for attending to these gaps. Overall, we argue that future research should be more theoretically grounded while, at the same time, considering validation and the dynamic aspects of vulnerability.

2.1. Introduction

Floods affect billions of people worldwide (Zarekarizi *et al*., 2020). Indeed, according to the Emergency Events Database (CRED, 2019), around 50,000 people died and approximately 10% of the world population was affected by floods between 2009 and 2019. Due to population growth and climate change, more frequent and widespread floods are anticipated (Hirsch & Archfield, 2015; Leung *et al*., 2019). Therefore, flood risk management is required for mitigating potential damages.

Nowadays there is a consensus that risk (i.e., the potential for adverse impacts) is not driven solely by natural hazards (e.g., floods, droughts) but depends on the interactions between hazards, exposure, and vulnerability (IPCC, 2012, 2014). In this regard, vulnerability plays an important role in flood risk assessment. It encompasses multiple social, economic, physical, cultural, environmental, and institutional characteristics which influence the susceptibility of the exposed elements to the impact of hazards account (BIRKMANN *et al*., 2013). Due to its importance, the need to understand and assess flood vulnerability has been highlighted by international initiatives such as the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR, 2015).

In response to this, numerous studies have been undertaken to better understand flood vulnerability. Nevertheless, both the terminology and methodology used in these assessments are still a subject of discussion (Aroca-Jiménez *et al*., 2020). In fact, some consider vulnerability as being a function of exposure and susceptibility BALICA; DOUBEN; WRIGHT, 2009; IPCC, 2001; TURNER *et al*., 2003; UNDP, 2014), while others separate these concepts (Dilley *et al*., 2005; Fedeski & Gwilliam, 2007) as it is possible to be exposed to a hazard and not be vulnerable. For instance, a person may live in an area prone to natural hazards but have sufficient alternatives to modify the structure of their house to prevent potential losses (CARDONA *et al*., 2012).

A wide range of approaches have been proposed for assessing flood vulnerability. The most commonly used methods are stage damage functions (Papathoma-Köhle *et al*., 2012, 2017; Tarbotton *et al*., 2015), damage matrices (Bründl *et al*., 2009; Papathoma-Köhle *et al*., 2017), and vulnerability indices ((BIRKMANN, 2006; DE BRITO; EVERS; HÖLLERMANN, 2017; KAPPES *et al*., 2012; MOREIRA; DE BRITO; KOBIYAMA, 2021). The first two methods assess only the physical vulnerability, neglecting the social vulnerability of their inhabitants (Koks *et al*., 2015). However, the capacity of households to cope, adapt, and respond to hazards is equally important for assessing the potential impacts of floods floods (de Brito *et al*., 2018). Therefore, given the importance of holistic studies on vulnerability to ensure a better representation of reality, the use of vulnerability indices is recommended (Balica *et al*., 2013; Birkmann *et al*., 2013b; Fuchs *et al*., 2011; Nasiri *et al*., 2016). Indices serve as a summary of complex and multidimensional issues to assist decision-makers, to facilitate the interpretation of a phenomenon, and to increase public interest through a summary of the results. Flood vulnerability indices are, therefore, a tool for measuring the vulnerability degree throughout the aggregation of several indicators or variables. Despite their advantages, indices can present misleading messages if they are poorly constructed or misinterpreted. Hence, a clear understanding of the normalization, weighting, and aggregation methods used to build an index is required (MOREIRA; DE BRITO; KOBIYAMA, 2021).

Over the past few years, several review articles about flood vulnerability have been published. For instance, Rufat *et al.* (2015) reviewed 67 articles to identify the leading drivers of social vulnerability to floods. Rehman *et al.* (2019) and Fatemi *et al.* (2017) reviewed different methodologies used for assessing flood vulnerability. Jurgilevich *et al.* (2017) systematically reviewed 42 climate risk and vulnerability assessments. More recently, Diaz-Sarachaga and Jato-Espino (2020) evaluated 72 articles related to the appraisal of vulnerability in different types of hazards in urban areas. Some studies also analyzed different methods and indexed construction designs to understand which decisions have the greatest influence on the vulnerability outcomes. For instance, Nasiri *et al.* (2016) compared damage curves, computer modeling, and indicators to evaluate flood vulnerability. Similarly, Schmidtlein *et al.* (2008) and Tate (2012, 2013) examined the sensitivity of the results to changes in the construction of the vulnerability index.

Notwithstanding these advances, to the best of our knowledge, no study has conducted a systematic review of flood vulnerability indices with a focus on the different stages involved in the construction of flood vulnerability indices. The investigation of the methods used for normalizing, weighting, aggregation, and validation and the implications for each choice for vulnerability assessment have received little attention so far. In addition, even though there have been recent advancements in the field (e.g., CUTTER; DERAKHSHAN, 2020), the temporal dynamics of flood vulnerability have not been tackled by the existing reviews. This is particularly important given that certain adaptation policies and strategies may reduce short-term risk probability but increase long-term vulnerability and exposure (CARDONA *et al.*, 2012). Therefore, a better understanding of the methods used in each step of the index construction, the vulnerability temporal dynamics (e.g., preand post-flood), and the uncertainty involved is needed for advancing research on flood vulnerability assessments.

Considering the aforementioned gaps, and given the proliferation of methods for building vulnerability indices, it is pertinent to review the development of this field. Hence, here, we carried out a systematic literature review of indices used to assess flood vulnerability. The focus is given to urban and riverine floods. The following questions guided the analysis: (1) which spatial scale was considered? (2) Which indicators were most commonly used to measure flood vulnerability? (3) How were the temporal dynamics of vulnerability addressed (e.g., pre- or post-flood event)? (4) Which methods were most commonly applied in each stage of the index building process (i.e., normalization, weighting, or aggregation)? (5) To which extent did these studies conduct validation and apply uncertainty and sensitivity analysis? In addition to highlighting existing challenges, we also point out directions for further research.

2.2. Overview of indicators and indices

In general, indicators consist of various pieces of data capable of synthesizing the characteristics of a system. When these indicators are aggregated, they are called index or composite indicators (SAISANA; TARANTOLA, 2002). Overall, the construction of an index comprehends seven steps (Figure 2-1). First, the phenomenon to be measured is defined, so that the index results can provide a clear understanding of this phenomenon (NARDO *et al.*, 2008). Then, the indicators used to measure the phenomenon are selected. This should be done carefully as the results reflect the quality of the selected indicators.

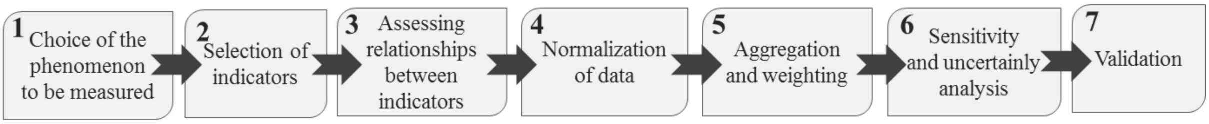

Figure 2-1 - Overview of the different steps involved in constructing an index.

In the third step, the relationships between the selected indicators are identified. Indicators with similar characteristics can be grouped, aiming to reduce the number of variables. To this end, statistical analysis (e.g., principal component analysis – PCA) or expert knowledge can be used to decide whether the indicators are sufficient or appropriate for describing the phenomenon (NARDO *et al.*, 2008). After selecting the indicators, they need to be normalized to a common scale before being aggregated into an index as they usually have different units of measurement (see Table 2-1 for the main normalization methods). By doing so, problems with outliers can also be reduced (JACOBS; SMITH; GODDARD, 2004).

Table 2-1 - Characteristics of the main normalization methods used for building indices.

Method	**Equation**	**Description**	**Reference**
Ranking	$y_{in} = \mathrm{Rank}(x_{in})$	Based on ordinal variables that can be turned into quantitative variables.	Carlier *et al.* (2018)
Z-scores	$y_{in} = \frac{x_{in} - \bar{x}_{in}}{\sigma_{\bar{x}_{in}}}$	Converts all indicators to a common scale with a mean of zero and a standard deviation of one.	Gerrard (2018)
Min-Max	$y_{in} = \frac{x_{in} - \min(x_{in})}{\max(x_{in}) - \min(x_{in})}$	Rescales values between 0 (worst rank) and 1 (best rank). It subtracts the minimum value and divides it by the range of the maximum value subtracted by the minimum value.	Jha and Gundimeda (2019)
Distance from the group leader	$y_{in} = \frac{x_{in}}{\max(x_{in})}$	Rescales values between 0 and 1. It is defined as the ratio of the value of the indicator to its maximum value.	Munyai *et al.* (2019)
Division by total	$y_{in} = \frac{x_{in}}{\sum(x_{in})}$	It is defined as the ratio of the value of the indicator to the total value for the indicator	Jamshed *et al.* (2019)
Categorical scale	$y_{in} = \begin{cases} 0 \text{ if } x_{in} < P^{15} \\ 20 \text{ if } P^{15} \leq x_{in} < P^{25} \\ 40 \text{ if } P^{25} \leq x_{in} < P^{65} \\ 60 \text{ if } P^{65} \leq x_{in} < P^{85} \\ 80 \text{ if } P^{85} \leq x_{in} < P^{95} \\ 100 \text{ if } x_{in} \leq x^{t}_{qc} \end{cases}$	Assign a value for each numeric or qualitative indicator. Values are based on percentage.	Andrade and Szlafsztein (2018)
Binary standard	None	It is calculated using simple Boolean 0 and 1 (false and true) values.	Garbutt *et al.* (2015)

Note: y is the transformed variable of x for indicator i for unit n. P^i is the i-th percentile of the distribution of the indicator x_{in}, and pan arbitrary threshold around the mean.

The fifth step comprises the weighting and aggregation of the indicators. Weights can be assigned to indicators to demonstrate their importance in relation to the studied phenomenon (see Table 2-2 for the main weighting methods). Given that it may be difficult to find an acceptable weighting scheme, equal weights are often used, which implies that all criteria are worth the same (DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018). Alternatively, an equal weighting scheme could be the result of a lack of knowledge about the indicators' importance. After the indicators are weighted, they are aggregated. The most common aggregation methods are linear and geometric. The linear method consists of the weighted and normalized sum of indicators, whereas the geometric aggregation represents the output of the indicators for which the exponent is their assigned weight (NARDO *et al.*, 2008).

The sixth step consists of sensitivity and uncertainty analyses (see Table 2-3 for the main uncertainty and sensitivity methods). The first evaluates the contribution of the uncertainty source of each indicator to the variance of the results, while the latter focuses on how the uncertainty of each indicator propagates through the index structure and affects the outputs (SAISANA; TARANTOLA, 2002; SAISANA; TARANTOLA; SALTELLI, 2005).

Table 2-2 - Characteristics of the main weighting methods used for building indices.

Type	Method	Description	Reference
-	Equal weighting	All indicators receive the same weight.	Hernández-Uribe *et al.* (2017)
Statistically-based	Principal component analysis (PCA) / Factor Analysis	PCA is used for factor extraction. The weights are obtained from the rotated factor matrix since the area of each factor represents the proportion of the total unit of the variance of the indicators that is explained by the factor.	Gu *et al.*(2018)
	Entropy method	Weights are assigned based on the degree of variation of the indicator values.	Lianxiao and Morimoto (2019)
Participatory or expert-based	Expert opinion	Experts agree on the contribution of each indicator for the studied problem.	Shah *et al.* (2018)
	Public opinion	They focus on the notion of people's concern about certain problems measured by the indicators.	Schuster-Wallace *et al.* (2018)
	Multi-criteria decision-making (MCDM)	It is a set of methods based on multiple criteria and objectives for structuring and evaluating alternatives.	de Brito *et al.* (2018)

Table 2-3 - Characteristics of the main methods for uncertainty and sensitivity analysis used for building indices.

Method	Description	Reference
One-at-a-time sensitivity analysis	By changing input data parameters, it was verified how these disturbances affected the results when all the other parameters remained constant.	de Brito *et al.* (2019)
Monte Carlo simulation	Computational algorithm which uses a probabilistic method that uses repeated random sampling	Feizizadeh and Kienberger (2017)
Statistical tools	Use of statistical tools such as regression, correlation analysis and cross-validation	Moreira *et al.* (2021), Nazeer and Bork (2019)

The final step comprises the validation of the index results. This is crucial for verifying if they are consistent with the real system and have a satisfactory precision range. Validation can be achieved by using independent secondary data that refer to observable outcomes. Since vulnerability is not a directly observable phenomenon, its validation requires the use of proxies such as mortality and built environment damage (SCHNEIDERBAUER; EHRLICH, 2006), post-event surveys (FEKETE, 2009), number of disasters (DEBORTOLI *et al.*, 2017), and emergency service requests (Kontokosta & Malik, 2018).

2.3. Methods

A bibliographic search was performed by focusing on studies that constructed flood vulnerability indices. The Web of Science (WoS) database was used to identify peer-reviewed articles published since 1945, using the following Boolean keywords: ("flood" OR "flooding") AND ("index" OR "composite indicator") AND ("vulnerability" NOT "coast*"). Only the abstract, title, and keywords were searched. This narrowed the search space substantially.

These queries elicited over 348 articles published between January 2002 and December 2019. At first, the title, abstract, and keywords were screened manually to exclude articles that were not useful for the purpose of the present study. After this preselection, the full text of 84 selected papers was revised in detail. An additional 11 key articles were included. They were not found in our original search even though they built vulnerability indices. This occurred because the keywords "index" or "composite indicator" were not mentioned in the article's abstract, title, or keywords. Hence, this limitation should be acknowledged, as relevant articles may have been disregarded.

Following their selection, the articles were classified according to (1) publication year, (2) study area country, (3) spatial scale (e.g., neighborhood, household, or city), (4) region classification (e.g., urban, rural[1], or both), (5) number of indicators, (6) whether or not there was a reduction in the indicators (e.g., PCA and expert knowledge), (7) temporal dynamics (pre- or post-flood), (8) normalization, aggregation, and weighting methods used, and (9) if there uncertainty and validation analysis were performed. A complete list of the reviewed papers is presented in the Appendice Table A1.

2.4. Results and discussion

2.4.1. Flood vulnerability indices at a glance

An increasing number of studies that built flood vulnerability indices can be observed in recent years, with about 80% (n = 76) of the articles being published since 2015 (Figure 2-2), which is also the year that the Sendai Framework for Disaster Risk Reduction

[1] Here, rural areas are defined as sparsely populated areas, whereas urban areas are considered densely populated regions.

(UNISDR, 2016) was agreed among several member states. Therefore, the growing number of publications may result from the increasing awareness of flood disaster prevention and reduction policies. The increasing number of vulnerability indices studies could also be attributed to the ease of using indices to address complex and multidimensional issues such as flood vulnerability in contrast to methods that demand more data (e.g., damage curves). Alternatively, this increase may just match a general rise in published papers. To investigate this, we calculated the increase in flood vulnerability studies in relative terms, based on a normalization according to the number of all flood publications in the WoS database. Results show that the increase in research on flood vulnerability indices is significantly greater than the increase in published flood articles (Appendice Figure A1).

(a)

(b)

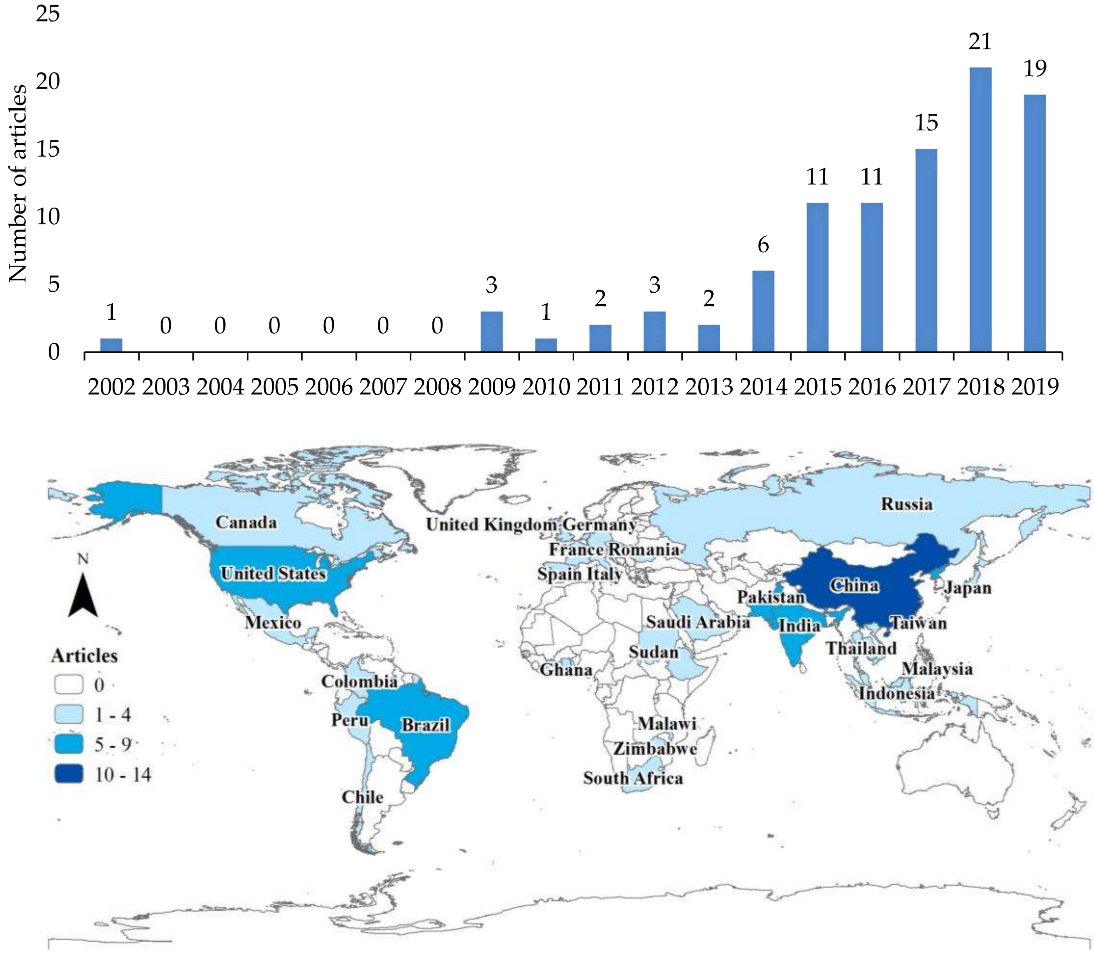

Figure 2-2 - Flood vulnerability index studies. (a) Temporal distribution from 2002 to 2019. For the standardized number of articles according to the total number of publications in the WoS database, see Appendix A (Fig. A1). (b) Geographical distribution.

Overall, most of the assessments were conducted in Asia (45.3%), followed by the Americas (24.2%), and encompassing 38 countries (Figure 2-2b). This was expected as, according to the Emergency Events Database (EM-DAT) statistics, between 2002 and 2019 Asia showed the highest number of deaths caused by floods (1027 deaths; CRED, 2019). As such, the studies are highly concentrated in a few countries, namely China (n = 14), Brazil (n = 8), India (n = 6), Pakistan (n = 6), and the United States (n = 6). Meanwhile, there were fewer studies in East and West Africa, despite the frequent occurrence of floods and the high mortality they cause across these regions.

In terms of spatial scale, most of the studies were conducted at the neighborhood scale (62.1%), followed by city (14.7%), household (12.6%), group of cities (7.4%), various scales (2.1%), and state scale (1.1%). Similar outcomes were obtained by Diaz-Sarachaga and Jato-Espino (2020), who found out that vulnerability studies at national and regional scales are infrequent. The neighborhood scale was the dominant scale in all continents (Figure 2-3) as it is the smallest unit for which data are available for large areas, generally through census data. Only eight studies (8.4%) were conducted at the basin level (i.e., group of cities), and a few articles (n = 2) conducted assessments across various scales. For instance, Balica, Douben and Wright (2009) evaluated the vulnerability at the basin, subbasin, and city scales. Similarly, Remo *et al.* (2016) compared three scales (i.e., census blocks, communities, and counties) and found out that the results generally mirrored each other. None of the considered articles draw conclusions at the national or global level.

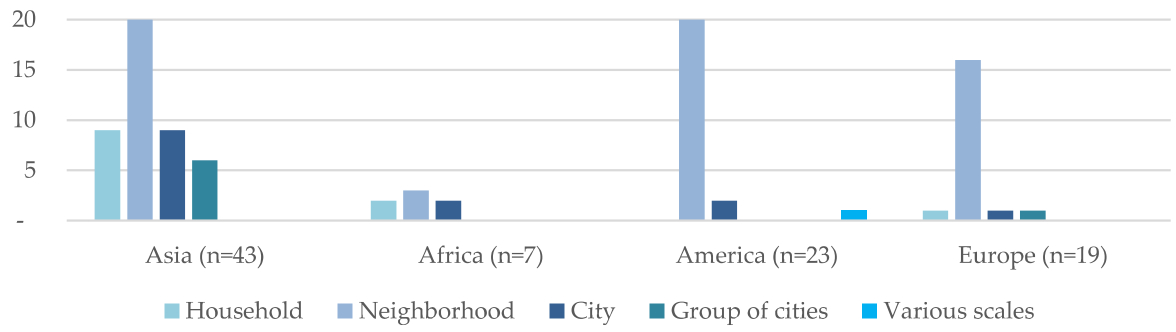

Figure 2-3 - Classification of papers of flood vulnerability in terms of scale in continents.

Around 40.0% of the studies were applied to urban areas, 15.8% to rural areas, and 44.2% to both. The high prevalence of studies that consider both urban and rural areas is related to the data availability, as the census tracks usually encompass the entire perimeter of a municipality. At the neighborhood scale, most studies considered only urban areas (53.4%; Figure 2-4). Conversely, studies at the household scale were developed mainly in rural areas

(58.3%). This can be explained by a lower availability of detailed geospatial data in rural areas worldwide (ZHANG; ZHU, 2018; ZIELSTRA; ZIPF, 2010). Therefore, in these cases, it is necessary to collect data via household surveys.

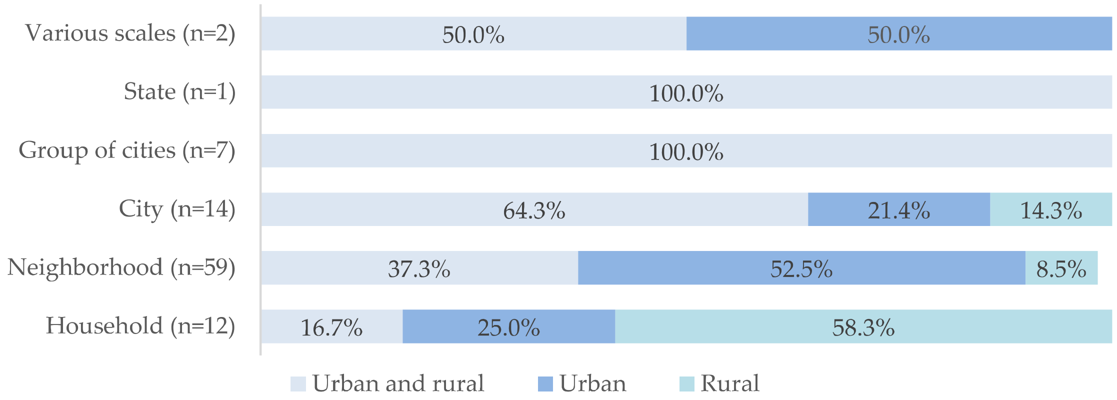

Figure 2-4 - Classification of studies in terms of rural and urban areas and spatial scale.

2.4.2. Indicators used to characterize flood vulnerability

Table 2-4 shows the most frequent indicators grouped into social, economic, physical, and coping capacity dimensions. In summary, social and economic indicators such as population density (37.9%), illiteracy rate (32.6%), unemployment rate (29.5%), female rate (28.4%), per capita income (25.3%), and elderly rate (22.1 %) were the most commonly used vulnerability indicators (Table 4). This is similar to the results obtained by Rufat *et al.* (2015), who found out that the most used indicators are poverty and deprivation, per capita income, unemployment rate, the elderly, and children. Nevertheless, widely used indicators found by the authors were not identified or were rarely used in our sample. These include, for example, stress and mental health, hygiene and sanitation, social networks, and experience with floods (SCHNEIDERBAUER; EHRLICH, 2006).

The studies used a average of 16 indicators. Although 32.6% (n = 31) of the studies used more than 20 indicators (e.g., SAM *et al.*, 2017), most of them (58.0%) did not apply any method for reducing the number of variables. Among the studies which conducted reduction, the most used technique was the PCA, which was applied to 35.5% (n = 11) of the indices that used more than 20 indicators (e.g., AROCA-JIMENEZ *et al.*, 2017; AROCA-JIMENEZ *et al.*, 2017; TÖRÖK, 2018). In addition to PCA, some studies used other approaches, for example, based on expert opinion (e.g., (DE BRITO; EVERS; DELOS

SANTOS ALMORADIE, 2018) or based on indicators with a high Pearson correlation (e.g., KOTZEE; REYERS, 2016).

Table 2-4 - Most commonly used flood vulnerability indicators. Only indicators used in at least five articles are shown here.

Dimension	**Indicator**	**N of articles**
Social	Population density	36 (37.9%)
	Illiteracy rate	31 (32.6%)
	Unemployment rate	28 (29.5%)
	Female rate	27 (28.4%)
	Elderly rate	27 (28.4%)
	Education level	23 (24.2%)
	Male rate	11 (11.6%)
	Children rate	11 (11.6%)
	Inhabitants aged 0-15	11 (11.6%)
	Population growth	10 (10.5%)
	Total population	9 (9.5%)
	Persons with disabilities	7 (7.4%)
	Family members	7 (7.4%)
	Single parents with young children	6 (6.3%)
	Household headed by females	6 (6.3%)
	Cultural heritage	5 (5.3%)
	Household member with illness	5 (5.3%)
	Children mortality	5 (5.3%)
Economic	Per capita income	24 (25.3%)
	Gross domestic product (GDP) per capita	11 (11.6%)
	Population poor	10 (10.5%)
	Rented houses	10 (10.5%)
	Household income	9 (9.5%)
	Dependency rates	9 (9.5%)
	Own vehicle	8 (8.4%)
	Percent of homeownership	5 (5.3%)
Physical	Household without sanitation	19 (20.0%)
	Household without safe water	14 (14.7%)
	Building material	14 (14.7%)
	Road network	12 (12.6%)
	Physical conditions of the building	11 (11.6%)
	Building location	9 (9.5%)
	Population in flood area	9 (9.5%)
	Urban area	8 (8.4%)
	Household without electricity	8 (8.4%)
	Number of floors	6 (6.3%)
	Building age	5 (5.3%)
	Building type	5 (5.3%)
	Number of hospitals	5 (5.3%)
Coping capacity	Early warning system	11 (11.6%)
	Past flood experience	7 (7.4%)
	Emergency committee	5 (5.3%)
	Flood insurance	5 (5.3%)

2.4.3. Temporal dynamics

In order to identify if the articles included the temporal dynamics of vulnerability, the indices were classified into pre-event (before), event (during) and post-event (after; KOBIYAMA *et al.*, 2006). Most of the studies focused on assessing past vulnerability trends (88.4%) and only 12.6% explored post-event flood vulnerability (e.g., (CARLIER *et al.*, 2018; MIGUEZ; VERÓL, 2017). None focused on the vulnerability during the event or elaborated on projections for future vulnerabilities.

Table 2-5 - Indicators used for flood vulnerability assessment through post-event approach.

Damage Type	Indicator	Reference(s)
Human	Human deaths	Chaliha *et al.* (2012); Baeck *et al.* (2014); Abbas *et al.*, (2018)
	Injured family members or human losses	Abbas *et al.* (2018); Ahmad and Afzal (2019)
	People suffering from poor health conditions due to floods	Chaliha *et al.* (2012), Jamshed *et al.* (2019)
	Population affected	Chaliha *et al.* (2012)
	Displacement	Okazawa *et al.* (2011)
	Domestic violence after a flood	Abbas *et al.* (2018)
	Left house due to flood	Abbas *et al.* (2018)
	Vulnerability to the dissemination of water borne diseases	Abbas *et al.* (2018); Miguez and Veról (2017)
	Access to safe water after a flood	Jamshed *et al.* (2019)
	Access to sanitation after a flood	Jamshed *et al.* (2019)
	Degradation of water quality	Jamshed *et al.* (2019)
Economic	Affected villages	Chaliha *et al.* (2012), Jamshed *et al.* (2019)
	Crop lost value	Chaliha *et al.* (2012)
	Economic loss regarding animal husbandry	Ahmad and Afzal (2019)
	House damage value	Chaliha *et al.* (2012)
	Borrowed money	Abbas *et al.* (2018)
	Decrease in food expenditure	Abbas *et al.* (2018)
	Increase in medical cost	Abbas *et al.* (2018)
Material	Area affected by flood	Chaliha *et al.* (2012); Carlier *et al.* (2018); Okazawa *et al.* (2011)
	Building damage	Chaliha *et al.* (2012); Carlier *et al.* (2018); Bertilsson *et al.* (2019), Jamshed *et al.* (2019)
	Damages to public utilities	Chaliha *et al.* (2012)
	Number of killed livestock's	Chaliha *et al.* (2012)
	Crop damage	Abbas *et al.* (2018), Jamshed *et al.* (2019)
	Damage to house, livestock and, assets	Abbas *et al.* (2018), Jamshed *et al.* (2019)
	Schools damaged by flood	Jamshed *et al.* (2019)

The indicators used are different according to the temporal scale considered. Post-event indices encompassed human, economic, and material damages to quantify the flood vulnerability (Table 2-5). Variables such as mitigation, damages, and coping behavior after experiencing a flood were often considered (ABBAS *et al.*, 2018). For instance, Rogelis *et al.*

(2016) compared the results of the most vulnerable areas by ranking the basins according to the observed impacts from highest to lowest damage in terms of number of fatalities, injured people, evacuated people, and number of affected houses.

2.4.4. Indicator normalization, weighting, and aggregation

Concerning the indicators normalization, the most used approach was min–max (30.5%), followed by Z score (12.6%) and distance from the group leader (12.6%; Table 2-6a). A total of five studies applied other methods. For example, Aroca-Jimenez *et al.* (2017, 2018) expressed the indicators' values in percentage or per capita value, and de Brito *et al.* (2018) used fuzzy functions to normalize the indicators. It is important to note that most papers did not specify the normalization method used (11.6%), which limits the reproducibility of the study results.

Among the weighing approach types, statistical methods were the most applied (30.5%), especially the PCA method (21.1%). The high use of PCA can be attributed to the pioneering work by Cutter *et al.* (2003), who recommended the use of a factor analytic approach. Other less common statistical methods include dividing the indicator values by the total or maximum value (OKAZAWA *et al.*, 2011), hot spot analysis (KUBAL *et al.*, 2009), and the unequal weighting method (KABLAN; DONGO; COULIBALY, 2017).

Table 2-6 - (a) Normalization methods; and (b) weighting methods.

a

Normalization Method	N	%
Min-Max	29	30.5
Z-score	12	12.6
Distance from the group leader	12	12.6
Unspecified	11	11.6
None (All indicators had the same unit)	11	11.6
Ranking	7	7.4
Categorical scale	3	3.2
Binary standard	3	3.2
Division by total	2	2.1
Others	5	5.3
	95	100

b

Type	Weighting Method	N	%
Statistically-based methods	PCA – weighting by factor scores	17	17.9
	PCA – equal weighting	3	3.2
	Entropy method	1	1.1
	Other statistical methods	8	8.5
Participatory or expert-based methods	Analytical Hierarchy Process	10	10.5
	Public opinion	6	6.3
	Expert opinion	2	2.1
	Other MCDM techniques	3	4.2
Others	Equal weighting	23	24.2
	Other methods	7	7.4
	Defined by the authors	8	8.4
	Unspecified	6	6.3
		95	100

Many authors recommend the use of participatory methods for weighing the indicators, such as the use of multicriteria decision-making (MCDM) tools (EVERS *et al.*, 2018). It is assumed that, if practitioners and experts are involved in creating an index that they find useful, it is more likely that they will trust its results (OULAHEN *et al.*, 2015). Furthermore, participation is believed to be a key component in fostering effective disaster risk reduction (FEKETE *et al.*, 2021). In the present study, the analytical hierarchy process (AHP) was the most common MCDM technique, which corroborates the results by de Brito and Evers (2016). These authors attributed this preference to the fact that AHP is a straightforward and flexible method. This method was applied separately in 10 papers and together with other methods in five papers, totaling 16.0% of the reviewed articles. Among the less common MCDM methods, Promethee (Preference Ranking Organization METHod for Enrichment of Evaluations; DAKSIYA *et al.*, 2017) and the analytical network process (DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018) techniques are worth mentioning.

A total of seven articles used other weighting methods, including the entropy method (LIANXIAO; MORIMOTO, 2019), Delphi technique (YANG *et al.*, 2018), and expert scoring (WU *et al.*, 2015). Furthermore, about one-quarter (24.2%) of the papers attributed equal weighting, and 6.3% did not specify the weighting method used (Table 2-6b). Some authors preferred not to weight indicators because they assumed that these indicators are equally important for the vulnerability calculation (YOON, 2012), whereas others pointed out that there is insufficient evidence to attribute importance to one factor over another (FEKETE, 2011).

In terms of aggregation, the majority of the articles (80.0%) used linear aggregation, followed by geometric aggregation (10.5%) and mixed methods (4.2%). The linear method is useful when all indicators have the same unit or after they have been normalized. The geometric aggregation is preferred when the interest is assessing the degree of noncompensation between the indicators. In linear aggregation, compensation is constant, while in geometric aggregation the compensation is lower for indices with low values (NARDO *et al.*, 2008). Nevertheless, the geometric method has a limitation when indicators with very low scores are compensated by indicators with high scores (GAN *et al.*, 2017).

It is important to mention other aggregation methods used (5.3%). For instance, Abebe *et al.* (2018) used the Bayesian belief network, which is formed by a graphical network representing the cause–effect relationships between the different indicators (PEARL, 1988). YANG *et al.* (2018) applied the Shannon entropy method. More recently, Amadio *et al.* (2019) used a non-compensatory aggregation method to compensate for the low performance of one indicator with some higher performance of another indicator. Finally, Chiu *et al.* (2014) used the fuzzy comprehensive evaluation method to aggregate the indicators.

2.4.5. Uncertainty, sensitivity, and validation

Each step in the construction of flood vulnerability indices carries uncertainty (SAISANA; TARANTOLA; SALTELLI, 2005), which is added to the ones associated with the randomness of flood events (MERZ; KREIBICH; APEL, 2008). Therefore, to ensure a better index quality and verify the results' robustness, uncertainty analysis should be conducted. Despite its importance, only three (3.2%) of the reviewed papers performed uncertainty analysis. Nazeer and Bork (2019) observed variations in the final results that changed input variables, and Feizizadeh and Kienberger (2017) and Guo *et al.* (2014) applied a Monte Carlo simulation and set pair analysis, respectively.

With respect to the sensitivity analysis (SA), only nine papers (9.5%) performed it. Most articles applied local SA by comparing the results obtained by changing input methods, such as choosing different weights (MÜLLER; REITER; WEILAND, 2011; NAZEER; BORK, 2019; ROGELIS *et al.*, 2016), aggregation methods (FERNANDEZ *et al.*, 2016; NAZEER; BORK, 2019) or indicators (ROGELIS *et al.*, 2016; ZHANG; YOU, 2014), or indicators (ROGELIS *et al.*, 2016; ZHANG; YOU, 2014). In addition, Abebe, Kabir and Tesfamariam (2018) quantified sensitivity through variance reduction and mutual information. Spatial SA was conducted by de Brito, Almoradie and Evers (2019) by computing the vulnerability class switches when the indicator weights were changed. Only Feizizadeh and Kienberger (2017) performed the global sensitivity analysis.

Although the number of flood vulnerability studies has increased, few studies attempted to validate the obtained outcomes (FEKETE, 2009). Of the reviewed articles, only 11 (11.6%) validated the results, mostly using maps with flooded areas (n = 7), flood damage (n = 3), and expert opinion (n = 1).

2.5. Persisting gaps and future research

Despite the increasing amount of research on flood vulnerability indices since 2015, a series of persistent knowledge gaps of methodological nature were found in our systematic review (Table 2-7). Here, we summarize these gaps and provide a research agenda with needs that should be addressed in the future.

The first challenge refers to the spatial scale, as vulnerability is not only site specific but also scale dependent (CIUREAN; SCHRÖTER; GLADE, 2013). The choice of the spatial scale in the reviewed articles was mostly driven by data availability, and hence, most of them were applied at the neighborhood level using census tracks. Despite the availability of census data at the country level, there were no studies at the national level, and only eight papers (8.4%) constructed vulnerability indices using data at the basin scale. Nevertheless, these scales are often used for flood risk management and are necessary to enable the comparability of regions and to define hot spot areas where intervention is needed (BALICA; DOUBEN; WRIGHT, 2009; FEKETE; DAMM; BIRKMANN, 2010). Conversely, studies at the household level were rare in our sample (n = 12). Yet, aspects related to the citizens' coping capacities can only be captured at this spatial scale.

An additional issue is the problem of down- or upscaling that implies different levels of generalization. Hence, multilevel and cross-scale studies are needed. They allow for a better understanding of scale implications, including their benefits and drawbacks. A better understanding of urban–rural linkages is also required, instead of studying them in isolation. To this end, the framework proposed by Jamshed *et al.* (2020) could be used. This framework considers, either qualitatively or quantitatively, how rural–urban linkages can influence the occurrence of floods and how these shape the vulnerability of rural households. It considers rural areas not as secluded units but rather as being interlinked with cities.

A further gap is that indicators related to the populations' coping and adaptive capacity were rarely used. The focus was given to social indicators that increase people's vulnerability. Similar to the scale choice, the preference for these indicators is driven due to data availability, as social indicators (e.g., age and gender) are easily accessible. Nevertheless, the capacity of people to anticipate, cope with, resist, and recover from disasters is equally important for understanding the risk. In fact, even poor and vulnerable people have the capacity to cope (WISNER; GAILLARD; KELMAN, 2012). Therefore, when dealing with flood vulnerability, other relevant indicators, such as risk perception (CARLIER *et al.*, 2018) and past flood experience (BERINGER; KAEWSUK, 2018), are important. However, data on these are often not readily available, thus requiring local research, which demands time, financial resources, and a multidisciplinary team. Indeed, information on citizens' adaptive behavior and perception requires longitudinal or quasi-experimental studies that allow the capturing of behavioral dynamics over time (KUHLICKE *et al.*, 2020). For instance, recent advancements have been made by applying geostatistical methods to psychosocial survey data (GUARDIOLA-ALBERT *et al.*, 2020). As an alternative, people's risk perception could be derived from widely available data sources, including, for instance, Google trends (e.g., Kam *et al.* 2019) and Twitter statistics (DYER; KOLIC, 2020). Nevertheless, it should be noted that such approaches can be considered only where the use of social media and search engines are prevalent across the society. In countries where the use of digital technologies is not widespread, there is the risk that the marginalized population is left out of the analysis.

Still with regard to the indicators used, many studies used variables that thematically overlap with each other. In this context, some indices used more than 20 indicators to measure flood vulnerability and did not apply any technique (e.g., PCA or expert based) to reduce this number. This can decrease the explanatory power of the index. In this context, besides PCA, the potential exists to apply dimensionality reduction techniques such as the t-distributed stochastic neighbor embedding (t-SNE; ANOWAR *et al.*, 2021). A further issue is that the reason for variable selection was often not given, or it was justified based on previous studies, without taking into consideration the study area specificities or conceptual frameworks. Due to the difficulty and time involved in developing indicators, low-quality databases are normally used (FREUDENBERG, 2003). For adequate indicator selection, the analytical soundness, measurability, relevance to the phenomenon being measured, and the relationships to each other (e.g., interrelationships and feedback loops) should be taken into account. Furthermore, more theoretically grounded research is needed to generate robust evidence for selecting the input indicators.

Table 2-7 - Summary of the identified knowledge gaps and need for building flood vulnerability indicators.

Topic	Gaps	Research needs
Scale	The choice of the spatial scale is mostly driven by data availability There are few assessments at the national and local levels	More attention should be devoted to multilevel and cross-scale studies The understanding of how rural-urban linkages can influence the vulnerability requires further attention
Selection of indicators	The choice of the indicators is mostly driven by data availability Often no justification is provided for the selection of indicators Coping and adaptive capacity indicators were rarely used Assessments often use the same set of indicators for different scales and contexts, disregarding inherent discrepancies	Risk perception indicators should be considered Longitudinal or quasi-experimental studies that capture behavioral dynamics over time are needed Potential exists to derive data on risk perception from widely available data sources (e.g,. social media, newspapers, search engines) The selection of indicators should be scale and context specific Theoretically grounded research is needed to generate robust evidence for selecting the input indicators
Indicators reduction	Several studies used variables that thematically overlap with each other Indicator reduction techniques were hardly used	Dimensionality reduction techniques could be applied in future studies (e.g., t-SNE and PCA)
Dynamics	The vulnerability indices reviewed were static and represent a snapshot of vulnerability in time and space Assessments focus on current vulnerability conditions	Studies that assess post-flood and future vulnerability scenarios are needed Research on the inter-indicator relations is needed to understand how one indicator affects another
Normalization, aggregation, and weighting	Several articles did not indicate why a specific normalization, aggregation, and weighting technique was chosen There was an overreliance on the use of the AHP weighting method Studies comparing different normalization and weighting techniques were rare	Future studies need to be more rigorous and present the reasoning behind such choices Different alternatives for indicator weighting (e.g., expert-based, MCDM, and statistical approaches) can be compared
Sensitivity, uncertainty, and validation	Few vulnerability indices conducted any sort of validation, sensitivity, and uncertainty analysis	Technical and user validation should become more widespread; potential exists to apply global sensitivity analysis and spatial sensitivity analysis Analysis of the sensitivity of different modeling steps in the outcomes is needed (i.e., how different aggregation methods affect the outcomes)

All of the vulnerability indices reviewed here are static and represent a snapshot of vulnerability. Hence, they do not capture the complexities and temporal dynamics of vulnerability. Few studies focused on measuring flood vulnerability post-event. Nevertheless, the drivers of vulnerability can vary considerably over time. Results by Kuhlicke *et al.* (2011) and Reiter *et al.* (2018) show that the exposed citizens (e.g., the elderly and children) may be less vulnerable during the preparatory phase of a flood but highly vulnerable during the recovery phase. Hence, incorporating the phase of the flood disaster is key for improving the validity of vulnerability indices (RUFAT *et al.*, 2015). To account for temporal context, the indicators can be differentiated according to the different phases of a disaster, i.e., preparedness, response, and recovery phases. Such a phase-oriented approach could inform variable selection and weighting. In addition to this, there is a need for research looking into future vulnerabilities, and a forward-looking perspective is needed for preventive flood risk reduction (BIRKMANN *et al.*, 2013; GARSCHAGEN; KRAAS, 2010). These could make use of, for instance, population growth projections or employ tools such as qualitative futuring techniques (HOFFMAN *et al.*, 2021). Nevertheless, it is important to notice that this can further increase the uncertainty of the vulnerability modeling outcomes. Still, exercises like this can provide a glimpse of plausible futures.

Similar to the selection of the indicators, several articles did not indicate why a specific normalization and weighting technique was chosen. Additionally, some did not explicitly specify any normalization (11.6%) or weighting (6.3%) method. Nevertheless, the use of arbitrary techniques without testing different methods and their assumptions increases the subjective judgment error. Hence, it is imperative for future studies to be more rigorous and present the reasoning behind such choices. Furthermore, there was an overreliance on the use of the AHP weighting method, and studies comparing different normalization and weighting techniques were rare (7.4%). Future research should tackle this by exploring different alternatives for evaluating indicator weights (e.g., expert-based, MCDM, or statistical approaches) and compare the findings by means of validation and sensitivity analyses.

A final persisting gap is that few vulnerability indices conducted any sort of validation, sensitivity, or uncertainty analysis. Fewer than 14%of the studies validated the obtained results. To this end, impact data were often used (e.g., REZENDE *et al.*, 2019). Only 9.5% conducted sensitivity or uncertainty analysis. This can lead to vulnerability outputs that are incoherent with the local reality by either over- or underestimating the vulnerability. This, in turn, has direct implications for flood risk management. In this regard, Fekete (2009) points out the difficulty in finding empirical evidence about vulnerability because vulnerability is multidimensional and not directly observable. Thus, further research is needed on the validation of vulnerability outcomes (including technical and user validation) and analysis of the sensitivity of the contribution of individual indicators to the obtained results. The potential exists to apply a global sensitivity analysis, which is already widely applied for building composite indicators for other fields of study (LUAN *et al.*, 2017; SAISANA; SALTELLI, 2008).

Besides the aforementioned methodological gaps, it is important to emphasize that the theoretical framework adopted influences the methodological choices that are made when constructing vulnerability indices. Even though we have not analyzed the theoretical constructs used by each study, when reading the articles it became clear that several of them do not specify how they conceptualize vulnerability. Furthermore, there are ambiguities in how vulnerability is understood (KELMAN, 2018). For instance, some authors consider coping and adaptive capacity as components of flood vulnerability (e.g., DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018; FEIZIZADEH; KIENBERGER, 2017). Others include flood hazard characteristics or exposure (e.g., Carlier *et al.*, 2018; Chaliha *et al.*, 2012) as part of vulnerability. Hence, we argue that a stronger theoretical underpinning of research is needed for producing scientifically rigorous and comparable research. Within this context, future work could investigate how different terminologies and theoretical constructs are defined and applied across different flood vulnerability case studies. Future reviews could also look into the methodology used to collect information on vulnerability indicators (e.g., surveys and public databases) as this influences the choices that can be made at each stage of the index construction.

2.6. Conclusions

The present study reviewed 95 articles from 38 countries that constructed flood vulnerability indices. In summary, despite the increasing number of studies and advances made, the review has revealed and reconfirmed a number of persistent knowledge gaps. Temporal dynamic aspects of vulnerability were often disregarded. Only 11.6% of the studies focused on indicators that address post-event conditions related to flood damage and consequences, and none of them investigated future vulnerabilities. Coping and adaptive capacity indicators were frequently ignored, as obtaining these data demands time and effort. Most did not apply sensitivity (90.5%) and uncertainty analyses (96.8%) nor did they perform results validation (86.3%). This demonstrates a limitation in the reliability of these indices. It is clear from the literature that the challenge for further research is to foster the development of dynamic vulnerability assessments that consider the coping capacity of citizens and take the uncertainty involved in all steps of the index building process into account, including the selection of indicators, normalization, weighting, and aggregation. This is required in order to advance our understanding of flood vulnerability and support pathways towards flood risk reduction.

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Appendix

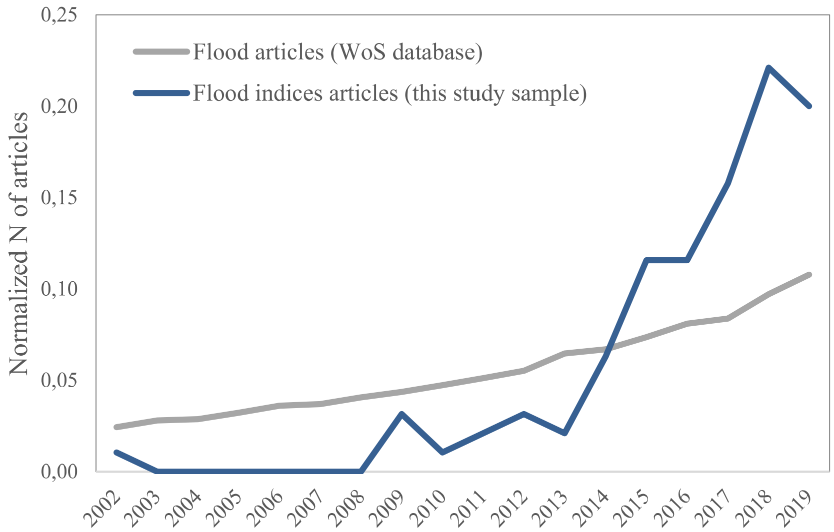

Figure A1 Normalized number of flood vulnerability indices and flood articles according to the Web of Science database. For the Flood articles search, the keyword "flood*" was used.

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
1	Abbas and Routray	2014	Sudan	Household	Urban and rural	20	None	Before	Categorical scale	Linear	Equal weighting	No	Yes
2	Abbas *et al.*	2018	Pakistan	Household	Rural	15	None	Both	Min-Max	Linear	PCA – weighted by factor scores	No	No
3	Abebe *et al.*	2018	Canada	Neighborhood	Urban	7	None	Before	Unspecified	Bayesian Belief Network (BBN)	Equal weighting	Yes (sensitivity)	Yes
4	Ahmad and Afzal	2019	Pakistan	Household	Both	36	None	Both	None (All indicators in the same unit)	Geometric	Equal weighting	No	No
5	Amadio, Mysiak and Marzi	2019	Italy	Neighborhood	Both	7	None	Before	None (All indicators in the same unit)	Non-compensatory aggregation	Equal weighting	Yes (fuzzy)	No
6	Andrade *et al.*	2018	Brazil	Neighborhood	Urban	11	None	Before	Categorical scale	Linear	Equal weighting	No	No
7	Antwi *et al.*	2015	Ghana	Neighborhood	Rural	22	None	Before	Ranking	Linear	None (selected by authors)	No	No
8	Armenakis *et al.*	2017	Canada	Neighborhood	Urban	15	None	Before	Distance from the group leader	Linear	None (selected by authors)	No	Yes
9	Aroca-Jimenez *et al.*	2017	Spain	Neighborhood	Urban	46	PCA	Before	Other (to porcentage or per capita)	Linear	PCA – weighted by factor scores	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
10	Aroca-Jimenez *et al.*	2018	Spain	Neighborhood	Urban	28	PCA	Before	Other (to porcentage or per capita)	Linear	PCA – weighted by factor scores	No	No
11	Baeck *et al.*	2014	South Korea	Group of cities	Urban and rural	16	None	Both	Z-score	Linear	PCA – weighted by factor scores	No	Yes
12	Balica *et al.*	2009	Romania, Germany and Cambodia	Various	Urban	66	None	Before	Distance from the group leader	Geometric	Equal weighting	No	No
13	Barros *et al.*	2015	Brazil	Neighborhood	Urban	13	None	Before	Min-Max	Linear	Equal weighting	No	No
14	Beringer and Kaewsuk	2018	Tailand	Household	Urban	48	None	Before	Min-Max	Linear	Equal weighting	No	No
15	Bertilsson *et al.*	2019	Brazil	Neighborhood	Urban	5	None	Both	None (All indicators in the same unit)	Geometric	Equal weighting	No	No
16	Carlier *et al.*	2018	France	City	Rural	17	PCA	After	Ranking	Linear	PCA – weighted by factor scores	No	No
17	Chakraborty and Mukhopadhyay	2019	India	Neighborhood	Both	16	None	Before	Ranking	Linear	Analytical Hierarchy Process (AHP)	No	Yes
18	Chaliha *et al.*	2012	India	Household	Rural	37	None	Both	Min-Max	Linear	Public opinion	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
19	Chen and Chen	2012	China	City	Urban	20	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP)	No	No
20	Chen and Leandro	2019	Germany	Neighborhood	Urban	7	None	Before	Unspecified	Linear	None (selected by authors)	Yes (sensitivity)	No
21	Daksiya *et al.*	2017	Indonesia	Neighborhood	Urban	7	None	Before	Min-Max	Linear	PROMETHEE-MCDA technique	No	No
22	Dandapat and Panda	2017	India	Neighborhood	Urban and rural	17	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP)	No	No
23	De Brito *et al.*	2018	Brazil	Neighborhood	Urban	11	Based of experts opinon (Delphi survey)	Before	Functions	Linear	Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP)	No	Yes
24	Debortoli *et al.*	2017	Brazil	City	Urban and rural	11	None	Before	Unspecified	Linear	None (selected by authors)	No	Yes
25	Erena and Worku	2019	Ethiopia	Household	Urban	24	None	Before	Min-Max	Geometric	Unequal weighting method	No	No
26	Feizizadeh and Kienberger	2017	Austria	Neighborhood	Urban and rural	17	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP)	Yes	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
27	Fekete	2009	Germany	Neighborhood	Urban and rural	41	PCA	Before	Ranking	Linear	Equal weighting	No	Yes
28	Fernadez *et al.*	2016	Portugal	Neighborhood	Urban	13	PCA	Before	Z-score	Linear	Equal weighted and PCA – weighted by factor scores	Yes (sensitivity)	No
29	Frolova *et al.*	2017	Russia	City	Urban and rural	10	None	Before	Distance from the group leader	Linear	Expert opinion	No	No
30	Fujiki and Renard	2018	France	Neighborhood	Urban	20	PCA	Before	Z-score	Linear	PCA – weighted by factor scores	No	No
31	Garbutt *et al.*	2015	England	Neighborhood	Urban and rural	53	None	Before	Binary standard	Linear	Equal weighting	No	No
32	Gerrard	2018	United Kingdom	Neighborhood	Rural	27	None	Before	Z-score	Linear	Unspecified	No	No
33	Ghosh and Kar	2018	India	Neighborhood	Urban and rural	12	None	Before	Ranking	Linear	Analytical Hierarchy Process (AHP)	No	No
34	Grosso *et al.*	2015	Portugal	Neighborhood	Urban and rural	39	PCA	Before	Division by total	Linear	PCA – weighted by factor scores	No	No
35	Gu *et al.*	2018	China	Neighborhood	Urban	18	None	Before	Unspecified	Linear	PCA – weighted by factor scores	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
36	Guo *et al.*	2014	China	City	Urban	16	None	Before	Unspecified	Geometric	Analytical Hierarchy Process (AHP) and entropy weight method	Yes	No
37	Hernández-Uribe *et al.*	2017	Mexico	Neighborhood	Urban	23	None	Before	Distance from the group leader	Geometric	Equal weighting	No	No
38	Ibrahim *et al.*	2017	Malaysia	City	Rural	6	None	Before	Unspecified	Linear	None (selected by authors)	No	No
39	Jamshed *et al.*	2019	Pakistan	Household	Rural	43	None	Both	Division by total	Linear	None method (select by authors)	No	No
40	Jha and Gundimeda	2019	India	District	Both	26	Yes	Before	Min-Max	Linear	Unspecified	No	No
41	Jung *et al.*	2014	South Korea	City	Urban and rural	11	PCA	Before	Z-score	Linear	Delphi technique	No	No
42	Kablan *et al.*	2017	Ivory Coast	Neighborhood	Urban	13	None	Before	Min-Max	Linear	Unequal weighting method	No	No
43	Kirby *et al.*	2019	Netherland	District	Both	25	Yes	Before	Min-Max	Linear	PCA – weighted by factor scores	No	No
44	Koks *et al.*	2015	Netherland	Neighborhood	Urban and rural	10	None	Before	Distance from the group leader	Linear	Equal weighting	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
45	Komi *et al.*	2016	Togo	City	Urban and rural	37	None	Before	Z-score	Linear	Analytical Hierarchy Process (AHP)	No	No
46	Kotzee and Reyers	2016	South Africa	City	Urban and rural	24	Pearson's correlation	Before	Min-Max	Linear	PCA – weighted by factor scores	No	No
47	Kubal *et al.*	2009	Germany	Neighborhood	Urban	16	None	Before	Binary standard	Linear	Hot Spot analysis	No	No
48	Lee and Choi	2018	South Korea	Neighborhood	Urban and rural	9	None	Before	Min-Max	Linear and geometric	Equal weighting	No	No
49	Lee and Choi	2019	South Korea	District	Both	6	None	Before	Min-Max	Linear and geometric	Equal weighting	No	No
50	Li *et al.*	2013	China	City	Urban	12	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP)	No	No
51	Lianxiao and Morimoto	2019	Japan	Neighborhood	Urban	11	None	Before	Min-Max	Linear	Entropy method	No	No
52	Liu and Li	2016	China	Household	Rural	8	None	Before	Min-Max	Linear	PCA – weighted by factor scores	No	No
53	Liu *et al.*	2018	China	Household	Rural	12	None	Before	None (All indicators in the same unit)	Linear	Equal weighting	No	No
54	Lotfata and Ambinakudige	2019	United States	Neighborhood	Both	15	None	Before	Ranking	Linear	Unspecified	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
55	Mavhura *et al.*	2017	Zimbabwe	Neighborhood	Rural	17	PCA	Before	Unspecified	Linear	Equal weighting	No	No
56	Miguez and Veról	2017	Brazil	Neighborhood	Urban	5	None	After	None (All indicators in the same unit)	Linear	Analytical Hierarchy Process (AHP)	No	No
57	Müller	2013	Chile	Neighborhood	Urban	12	None	Before	Distance from the group leader	Linear	Public opinion	No	No
58	Müller *et al.*	2011	Chile	Neighborhood	Urban	10	None	Before	Division by total	Linear	Public opinion	Yes (sensitivity)	No
59	Munyai, Musyoki and Nethengwe	2019	South Africa	Household	Rural	14	None	Before	Distance from the group leader	Geometric	Equal weighting	No	No
60	Mwale *et al.*	2015	Malawi	Neighborhood	Rural	37	None	Before	Unspecified	Linear	Public opinion	No	No
61	Nahiduzzaman *et al.*	2015	Saudi Arabia	Neighborhood	Urban	8	None	Before	Unspecified	Linear	Unspecified	No	No
62	Nasiri *et al.*	2019	Malaysia	District	Urban	25	None	Before	Unspecified	Linear	Analytical Hierarchy Process (AHP)	No	No
63	Nazeer and Bork	2019	Pakistan	District	Both	18	None	Before	Min-Max	Linear and geometric	Division by variance and PCA – weighted by factor scores	Yes	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
64	Nelson *et al.*	2015	United States	Neighborhood	Urban	38	PCA	Before	Z-score	Linear	PCA – weighted by factor scores	No	No
65	Nguyen and Nguyen	2019	Vietnamita	Neighborhood	Both	24	None	Before	Min-Max	Linear	Equal weighting	No	No
66	Ni *et al.*	2010	China	Neighborhood	Urban and rural	9	None	Before	Min-Max	Linear	Unspecified	No	Yes
67	Okazawa *et al.*	2011	Global	State	Urban and rural	11	None	Both	Distance from the group leader	Linear	Division by Max	No	No
68	Papathoma-Köhle, Schlögl and Fuchs	2019	Austria	Household	Urban	27	Yes	Before	Z-score	Linear	Division by total	No	No
69	Peng	2018	Taiwan	Neighborhood	Urban and rural	19	None	Before	None (All indicators in the same unit)	Linear	Analytical Hierarchy Process (AHP) and Delphi technique	No	No
70	Quezada-Hofflinger *et al.*	2017	Peru	Neighborhood	Urban	20	PCA	Before	None (All indicators in the same unit)	Linear	PCA – weighted by factor scores	No	No
71	Rahman *et al.*	2016	Saudi Arabia	Neighborhood	Urban	8	None	Before	Distance from the group leader	Linear	Equal weighting	No	No
72	Rana and Routray	2018	Pakistan	Neighborhood	Urban	34	None	Before	None (All indicators in the same unit)	Linear	None (selected by authors)	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
73	Remo *et al.*	2015	United States	Various	Urban and rural	17	PCA	Before	Min-Max	Linear	PCA – weighted by factor scores	No	No
74	Reyes-Olvera and Gutiérrez-González	2016	Mexico	City	Urban and rural	10	None	Before	None (All indicators in the same unit)	Linear	PCA – weighted by factor scores	No	No
75	Rezende *et al.*	2019	Brazil	Neighborhood	Urban	9	None	Before	Categorical scale	Linear	None (selected by authors)	No	Yes
76	Roder and Sofia	2017	Italy	Neighborhood	Urban and rural	16	PCA	Before	Z-score	Linear	PCA – equal weighting	No	No
77	Rogelis *et al.*	2016	Colombia	Neighborhood	Urban and rural	29	PCA	Both	Min-Max	Linear	PCA – equal weighting	Yes (sensitivity)	No
78	Roncancio and Nardocci	2016	Brazil	Neighborhood	Urban	24	PCA	Before	Z-score	Linear	PCA – equal weighting	No	No
79	Ronco *et al.*	2015	Switzerland	Neighborhood	Urban and rural	14	None	Before	Unspecified	Linear	Public opinion	No	No
80	Sam *et al.*	2017	India	Household	Rural	30	None	Before	Min-Max	Linear	Equal weighting	No	No
81	Schuster-Wallace *et al.*	2018	Canada	Neighborhood	Urban	8	None	Before	Distance from the group leader	Linear	Public opinion	No	No
82	Shah *et al.*	2018	Pakistan	City	Urban and rural	35	None	Before	None (All indicators in the same unit)	Geometric	Expert opinion	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
83	Shiau *et al.*	2012	Taiwan	Neighborhood	Urban and rural	5	None	Before	None (All indicators in the same unit)	Geometric	Division by total	No	No
84	Tapsell *et al.*	2002	United States	Neighborhood	Urban and rural	7	None	Before	Z-score	Linear	Equal weighting	No	No
85	Tate *et al.*	2016	United States	Neighborhood	Urban	12	None	After	Min-Max	Geometric	Division by total	No	No
86	Török	2018	Romania	Neighborhood	Urban and rural	28	PCA	Before	Z-score	Linear	PCA – weighted by factor scores	No	No
87	Wu *et al.*	2015	China	Group of cities	Urban and rural	9	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP) and expert scoring method	No	Yes
88	Xiong *et al.*	2019	China	City	Both	25	None	Before	Min-max	Linear	Analytical Hierarchy Process (AHP)	No	No
89	Yang *et al.*	2018	China	Neighborhood	Urban and rural	15	None	Before	Distance from the group leader	Fuzzy Comprehensive Evaluation Method (FCEM)	Delphi technique	No	No
90	Yang *et al.*	2018	China	Neighborhood	Urban and rural	16	None	Before	Distance from the group leader	Shannon entropy methods	Delphi technique	No	No

Table A1 - List of the reviewed papers.

Nº	Author(s)	Year	Study area country	Spacial scale	Region classification	Number of indicators	Reduction of indicators	Temporal dynamics	Normalization method	Aggregation method	Weighting method	Uncertainy and sensitivity analysis	Validation
91	Yoon *et al.*	2014	South Korea	Group of cities	Urban and rural	15	None	Before	Unspecified	Linear	Unspecified	No	No
92	Zachos *et al.*	2016	United States	Neighborhood	Urban and rural	15	None	Before	Ranking	Linear	Division by total	No	No
93	Zeng *et al.*	2016	China	Neighborhood	Rural	15	None	Before	Min-Max	Linear	Analytical Hierarchy Process (AHP) and entropy weight method	No	No
94	Zhang and You	2014	China	City	Urban and rural	36	PCA	Before	Min-Max	Linear	Equal weighting	Yes (sensitivity)	No
95	Zhang *et al.*	2018	China	Neighborhood	Urban	9	None	Before	Unspecified	Non-parametric DEA method	PCA – weighted by factor scores	No	No

CHAPTER 3

Effect of different normalization, aggregation, and classification methods on the construction of flood vulnerability indexes

This section is based on the following paper published in Water:

MOREIRA, L.L.; de BRITO, M.M.; KOBIYAMA, M. Effect of different normalization, aggregation, and classification methods on the construction of flood vulnerability indexes. Water, v. 13, 98, 2021.

Abstract: Index-based approaches are widely employed for measuring flood vulnerability. Nevertheless, the uncertainties in the index construction are rarely considered. Here, we conducted a sensitivity analysis of a flood vulnerability index in the Maquiné Basin, Southern Brazil, considering distinct normalization, aggregation, classification methods, and their effects on the model outputs. The robustness of the results was investigated by considering Spearman's correlations, the shift in the vulnerability rank, and spatial analysis of different normalization techniques (min-max, z-scores, distance to target, and raking) and aggregation methods (linear and geometric). The final outputs were classified into vulnerability classes using natural breaks, equal interval, quantiles, and standard deviation methods. The performance of each classification method was evaluated by spatial analysis and the Akaike's information criterion (AIC). The results presented low sensitivity regarding the normalization step. Conversely, the geometric aggregation method produced substantial differences on the spatial vulnerability and tended to underestimate the vulnerability where indicators with low values compensated for high values. Additionally, the classification of the vulnerability into different classes led to overly sensitive outputs. Thus, given the AIC performance, the natural breaks method was most suitable. The obtained results can support decision-makers in reducing uncertainty and increasing the quality of flood vulnerability assessments.

Keywords: aggregation; classification; composite indicators; flood vulnerability; normalization

3.1. Introduction

Vulnerability has an important role in flood risk assessment as hazards only become disasters if there are vulnerable people or infrastructure located in hazard-exposed areas

(KOBIYAMA; GOERL; MONTEIRO, 2018). Indeed, flood impacts strongly depend on the vulnerability of the exposed system or community (DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018; REILLY, 2009). Thus, the knowledge of vulnerability is fundamental for assessing flood risk as it allows computing the susceptibility of the exposed elements (KARAGIORGOS *et al.*, 2016) by considering multiple dimensions (BIRKMANN, J. *et al.*, 2013). Furthermore, the assessment of vulnerability allows identifying hot spot areas and the main drivers that contribute to it (e.g. social, economic, physical, cultural, environmental and institutional) (RUFAT *et al.*, 2015).

According to Nasiri *et al.* (2016), flood vulnerability is usually assessed by employing the following methods: (i) vulnerability curve, (ii) disaster loss data, (iii) computer modeling and (iv) index-based. The latter is recommended by several authors because it allows for a holistic analysis of the vulnerability dimensions, aiming to ensure a better representation of reality (BALICA. *et al.*, 2013; BIRKMANN, J. *et al.*, 2013; FUCHS; KUHLICKE; MEYER, 2011; NASIRI; MOHD YUSOF; MOHAMMAD ALI, 2016). Additionally, the use of indicators supports to simplify the system conditions and behavior, to summarize complex and multidimensional issues, to facilitate interpretations by end-users, and to reduce the number of indicators (SAISANA; TARANTOLA, 2002).

Despite the advantages of index-based approaches, there are some limitations as each step of the index construction carries uncertainty (JORGENSEN; BURKHARD; MÜLLER, 2013; NAZEER; BORK, 2019). Such uncertainties are mainly related to the normalization of indicators, criteria weighting, aggregation method as well as the quality and availability of data, natural variability, and human judgment (CHEN *et al.*, 2011; CROSETTO; TARANTOLA; SALTELLI, 2000; LIGMANN-ZIELINSKA; JANKOWSKI, 2014; MALCZEWSKI, 2006). They influence the final vulnerability patterns (TATE, 2012). Hence, the methodological choices made during the composite index construction implicate assumptions, subjectivity, and uncertainties that must be identified and recognized (BALICA; WRIGHT, 2010; NARDO *et al.*, 2008).

In order to understand the uncertainties and guarantee the robustness of flood vulnerability index assessments, the construction and stability of model outputs should be investigated under a wide range of possible conditions. In this regard, sensitivity and uncertainty analyses are needed (CHEN; LEANDRO, 2019; FERNANDEZ *et al.*, 2016).

Nevertheless, these analyses are seldom conducted in flood vulnerability studies (BURGASS *et al.*, 2017; DE BRITO; EVERS, 2016). Most of the published articles deal only with the uncertainty associated to the weighting process (BECKER *et al.*, 2017; CHEN; YU; KHAN, 2013; DE BRITO; ALMORADIE; EVERS, 2019; MÜLLER; REITER; WEILAND, 2011; ROGELIS *et al.*, 2016; XU; ZHANG, 2013) or deal with understanding the uncertainties in hazard models (LIU, Z.; MERWADE; JAFARZADEGAN, 2019; LIU, Zhu; MERWADE, 2018, 2019; RAJIB *et al.*, 2020). However, other steps that are also relevant, such as the uncertainty introduced by the normalization and aggregation (NAZEER; BORK, 2019; YOON, 2012), and the classification of the results into different vulnerability classes are understudied.

Previous researches have shown that sensitivity and uncertainty analyses applied to the normalization and aggregation steps are crucial to guarantee the robustness of flood vulnerability index (ABEBE; KABIR; TESFAMARIAM, 2018) as they can strongly influence the outputs. The choice of methods can mask the real vulnerability by over- or under-estimating its values. Moreover, the classification process of the flood vulnerability map results in different outcomes as demonstrated by studies focusing on landslide susceptibility (BAEZA; LANTADA; AMORIM, 2016), and intelligent compaction data (MAZARI *et al.*, 2017). Indeed, some studies (FLORIDI *et al.*, 2011; TALUKDER; HIPEL; VANLOON, 2017) found that the use of different normalization methods influences the final composite indicator. Similarly, Caccavale and Giuffrida (2020) argued that, after weighting, normalization, database, and aggregation are the main sources of output variation. In contrast, Santeramo (2015) showed that normalization and weighting have a minimal effect on the construction of an index for food security and that attention should be paid to the database and aggregation steps.

Despite these studies, few researchers have addressed the uncertainty introduced by the use of different index construction methods in the context of flood vulnerability. Usually, attention is often paid to the uncertainty introduced by criteria weights (BECKER *et al.*, 2017; CHEN, Y.; YU; KHAN, 2013; DE BRITO; ALMORADIE; EVERS, 2019; MÜLLER, A.; REITER; WEILAND, 2011; ROGELIS *et al.*, 2016; XU; ZHANG, 2013). Nevertheless, the choice of the normalization, aggregation, and classification methods is usually done without transparency (DE BRITO; EVERS; HÖLLERMANN, 2017; RUFAT *et al.*, 2015). Therefore, the potential of different techniques in influencing the vulnerability assessment outcomes is still unclear.

To provide solutions for the aforementioned gaps, the present study aims to understand the flood vulnerability behavior by considering different normalization, aggregation, and classification methods in order to construct a robust flood vulnerability index. Here, the following questions are addressed: (i) Can the choice of normalization, aggregation and classification methods affect the outputs of flood vulnerability? (ii) How does the uncertainty of the flood vulnerability maps vary in space for each method choice? (iii) Which methods are more appropriate for building flood vulnerability indexes? The study case of the Maquiné river basin, located in the South of Brazil, is used to illustrate the proposed approach.

3.2. Materials and Methods

3.2.1. Study Area

The proposed methodology was applied to the Maquiné River Basin (510 km²), Southern Brazil (Figure 3-1). This basin is located in a mountainous area, and its altitude varies between 9 to 975 m. The climate is mostly humid subtropical. However, at altitudes above 700 m, the climate becomes humid temperate.

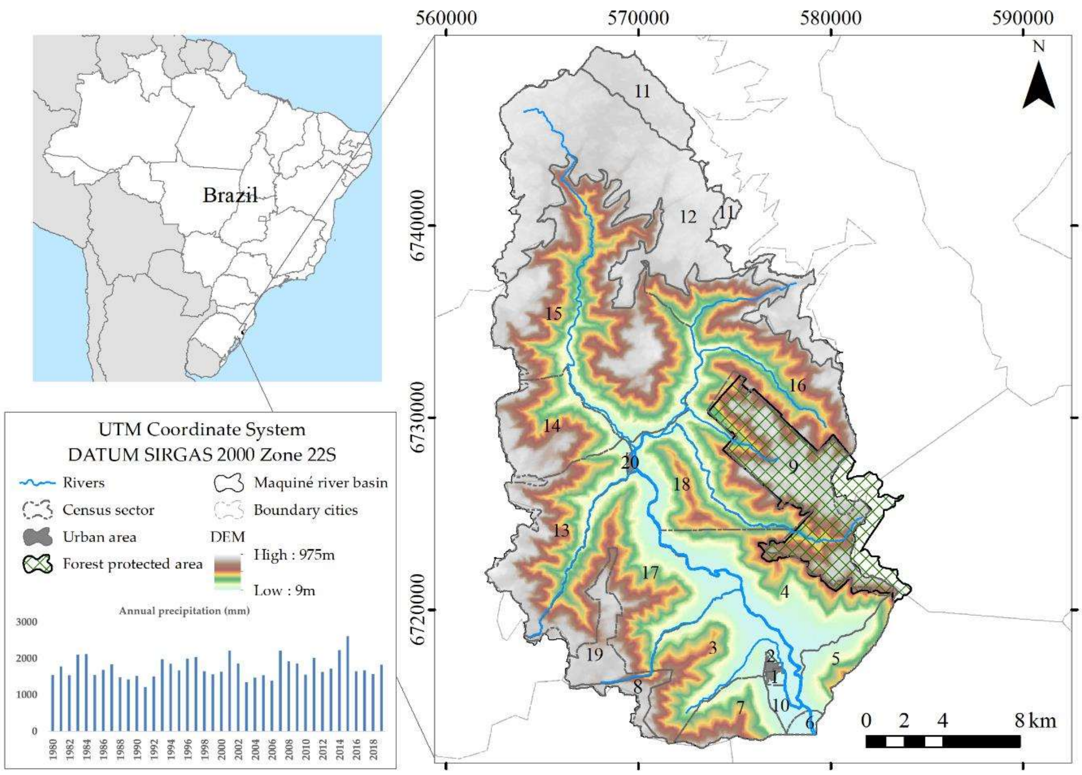

Figure 3-1 - Location of the Maquiné River Basin, census blocks (CB), DEM (digital elevation model), and annual precipitation (mm).

The mean annual rainfall is between 1700 and 2109 mm. The basin is mostly covered by forest (78.3%), followed by crops (11.7%), bare soil (5.5%), reforestation (3.0%), water (0.9%), and urban area (0.7%). The basin has a population of 6024 inhabitants, 70.0% of which live in rural areas (IBGE, 2010). This area is divided into twenty census blocks, where one is represented by a forest protection area. This basin was chosen as a case study because flood disasters occur annually or biannually, routinely affecting the citizens. One of the most significant events occurred in May 2008, when the river discharge reached 568 m^3/s, much higher than the average one (15.2 m^3/s), damaging houses and displacing people (DE CASTRO; MELLO, 2013).

3.2.2. Flood Vulnerability Index Construction

The construction of indexes usually consists of the following steps (Figure 3-2): (i) choice of the phenomenon to be measured; (ii) indicators selection; (iii) normalization; (iv) weighting; (v) aggregation; (vi) classification of the results in different classes; (vii) sensitivity and uncertainty analysis; and (viii) validation (NARDO *et al.*, 2008).

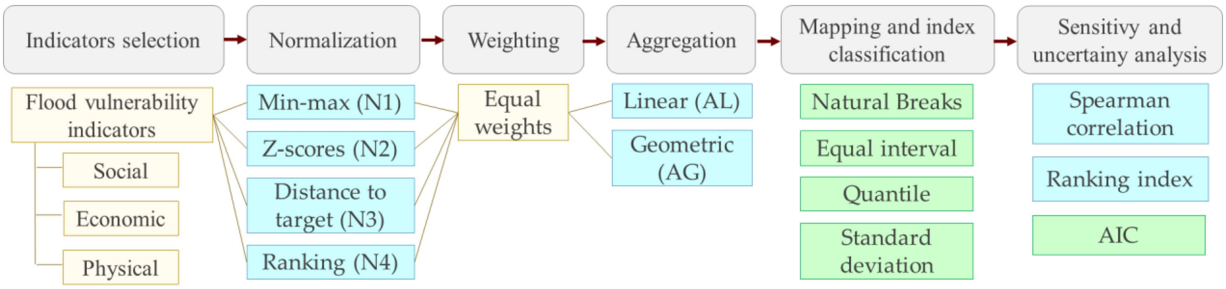

Figure 3-2 - Flowchart with the methodological outline. The uncertainty of the different normalization and aggregation methods was evaluated using both the Spearman correlation and the ranking index analysis (blue boxes). The uncertainty coming from the index classification step was evaluated by employing the Akaike's information criterion (AIC) analysis (green boxes).

In order to investigate uncertainty in the construction of a flood vulnerability index for our case study, we (i) chose relevant indicators based on a systematic literature review (CONTRERAS; CHAMORRO; WILKINSON, 2020; KIENBERGER; CONTRERAS; ZEIL, 2014); normalized these indicators by using the four most common methods (minmax, z-scores, distance to target, and raking); (iii) employed an equal-weights scheme; (iv) aggregated the normalized indicators with equal weights by two aggregation methods: linear and geometric; (v) classified flood vulnerability outputs by considering four methods; and (vi) performed a sensitivity and uncertainty analysis of the normalization and aggregation methods by computing the Spearman correlation between the outputs and the rankings using a box plot. Furthermore, the performance of the different classification methods was evaluated by using the Akaike's information criterion (AIC) (Figure 3-2).

The indicators used to represent flood vulnerability were selected according to: (i) their relevance, as evidenced by a systematic literature review conducted in a previous step of this research, (ii) the availability of data to represent them, and (iii) their suitability to the Brazilian context. Based on these criteria, we selected 19 indicators (Table 3-1). The datasets used to represent them were obtained from the Brazilian 2010 Census (2010). The spatial resolution of this data corresponds to the census block level (IBGE, 2010). Among the 20 census blocks in Maquiné River Basin, two were ignored (8 and 9, see Figure 3-1), because there are no people living there and, consequently, no vulnerability. The selected indicators were grouped into three vulnerability categories: social, economic, and physical (Table 3-1). Given to data availability limitations, relevant criteria such as distance to critical infrastructure and risk perception were not considered.

Table 3-1 - Input flood vulnerability indicators, their dimensions, and units.

Category	Indicator	Unit
Social vulnerability	Total population	persons
	Population density	persons km^2
	Number of women	persons
	Dependency rate*	percentage
	Households with more than 5 people	percentage
	Number of women head of homes	persons
	Inhabitants aged 0 to 4 years	persons
	Inhabitants aged more than 65 years	persons
	Illiterate people	persons
Economic vulnerability	Per capita income	1000/R$
	Unemployed people	persons
	People living in rented houses	persons
	Households' per capita monthly income equal 1/8 of the minimum wage	percentage
	Househead without income	percentage
	Househead's income less than 1 minimum wage	percentage
	Househead's income less than 2 minimum wages	percentage
Physical vulnerability	Households with open sewage	percentage
	Households without garbage collect	percentage
	Households without access to electricity	percentage

Indicators that quantify households were transformed to percentages (number of households divided by the total of households in the census block) to avoid misleading with the number of persons. Data source is Brazilian 2010 Census (2010). R$ denotes the Brazilian currency. * Dependency rate is an age–population ratio of persons that are not in the labor force (persons' ages 0 to 14 and 65+).

The indicators were normalized, (i.e., were changed into the same units) to allow their aggregation. The following methods were chosen, as proposed by Saisana and Saltelli (2011).

- Min-max - rescales values from 0 (worst rank for a specific indicator), to 1 (the best). It subtracts the minimum value and divides it by the range of the maximum value subtracts the minimum value;

$$y_{in} = \frac{x_{in} - \min(x_{in})}{\max(x_{in}) - \min(x_{in})} \tag{1}$$

- Z-cores - converts all the indicators to a common scale with a mean of zero and a standard deviation of one;

$$y_{in} = \frac{x_{in} - \bar{x}_{in}}{\sigma_{\bar{x}_{in}}} \tag{2}$$

- Distance to target - normalizes indicators by dividing the unit's value by a reference target (i.e. maximum value);

$$y_{in} = \frac{x_{in}}{\max(x_{in})} \tag{3}$$

- Ranking - based on ordinal variables that can be turned into quantitative variables.

$$\text{yin=Rank}(x_{in}) \tag{4}$$

where y_{in} is the normalized indicator; x_{in} is the indicator value; $\bar{x}_{in}$ is the indicator's average; and $\sigma_{\bar{x}_{in}}$ is the indicator standard deviation.

After normalizing the indicators, they were aggregated by two methods: linear and geometric, as showed by Equations (5) and (6), respectively. All the indicators had the same weight, thus receiving the same importance. This allowed focusing only on the uncertainties of normalization and aggregation methods because different weights would interfere in the final results.

$$\mathbf{Index} = \sum_{\mathbf{i=1}}^{\mathbf{q}} \mathbf{w_i I_i} \tag{5}$$

$$\mathbf{Index} = \prod_{\mathbf{i=1}}^{\mathbf{q}} \mathbf{x^{w_i}} \tag{6}$$

where $\sum_i^n w_i = 1$ and $0 \leq w_i \leq 1$, for all $i = 1, \dots, n$, and w is the weight associated with a normalized value (I) for the indicator i; and q is the number of indicators.

Finally, the flood vulnerability index was spatialized and classified into five categories: “very low”, “low”, “medium”, “high”, and “very high”. This classification was made by four methods:

- Natural breaks (Jenks) – class breaks are identified the best group similar values and that maximize the differences between classes. The features are divided into classes whose boundaries are set where there are relatively big differences in the data values;
- Equal interval – it divides the values into equal-sized classes. After specifying the number of intervals, the class breaks based on the value range are automatically determined;
- Quantile – each class contains an equal number of features;
- Standard deviation - shows how much a feature's attribute value varies from the mean. Class breaks are created with equal value ranges that are a proportion of the standard deviation, usually at intervals of one, one-half, one-third, or one-fourth standard deviations using mean values and the standard deviations.

3.2.3.Sensitivity Analysis

The uncertainty and sensitivity analysis or robustness test was conducted to understand how the variation in the output parameters can be apportioned to different choices of normalization and aggregation methods, as well as the index classification methods.

We tested the robustness of our results by changing input data parameters, considering a local sensitivity analysis (SA) termed one-at-a-time SA (DAMM, 2010). By variating the normalization, aggregation and classification methods, we verified how these disturbances affected the results when all the other parameters remained constant (LOUCKS; BEEK, 2017). The similarity of the outputs when considering these changes was measured by conducting a correlation analysis using the Spearman’s rank correlation (NAZEER; BORK, 2019; TALUKDER; HIPEL; VANLOON, 2017; YOON, D. K., 2012). This nonparametric correlation allows measuring the strength of the association between two variables (HAUKE; KOSSOWSKI, 2011). Additionally, we computed the sensitivity according to the rank methodology proposed by Hudrliková (2013) to examine the relative vulnerability ranking of the census block with different normalization and aggregation approaches.

To investigate the sensitivity of the different classification methods schemes and identify the most suitable one, we adopted the Akaike’s information criterion (AIC) (AKAIKE, 2011). At first, we mapped all the indexes by using all the classification methods to investigate the spatial differences. Then, the AIC was applied to the classification of geospatial data (MAZARI *et al.*, 2017) by using Equations (7) and (8).

$$\mathrm{AIC} = -2\sum_{K=1}^{m}\sum_{i\in G_k} x_i \log \hat{q}_k + 2(m-1) \tag{7}$$

where

$$\hat{q}_k = \sum_{i\in G_k} x_i / X n_k \tag{8}$$

where x_i is the geospatial data (index value); m is the number of classes; G_k is the kth class of data; X is the global sum of x_i data; and n_k is the number of data in class G_k.

3.3. Results

Based on four normalization and two aggregation methods, six flood vulnerability indexes or scenarios (N1AL, N2AL, N3AL, N4AL, N2AG, and N4AG) were generated. Two normalization methods were unable to be used with geometric aggregation, such as min-max and distance to target. The former transformed the minimum value to zero, resulting in a final vulnerability of zero. Similarly, with the distance to target method, it was possible only to aggregate indicators with non-zero values. It indicates that the geometric aggregation operator does not possess the ability to aggregate such types of information effectively (GARG *et al.*, 2018). In this case, it was necessary to exclude seven indicators that presented values equal to zero in some census blocks.

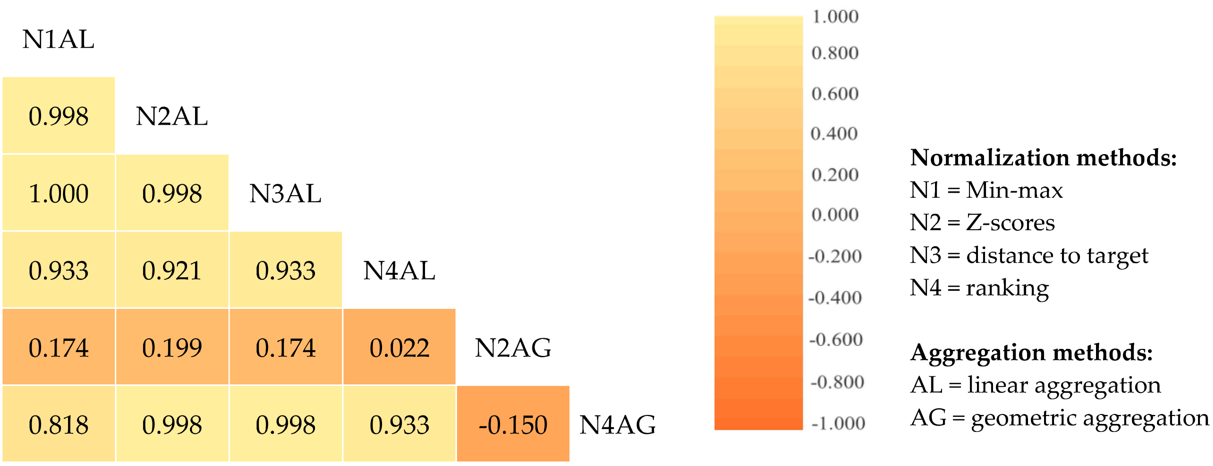

Figure 3-3 - Correlation between the flood vulnerability indexes based on the different normalization and aggregation methods. Numbers represent Spearman correlation coefficients; colors represent the strength of the correlation.

The correlations between the flood vulnerability indexes (Figure 3-3) show that the majority of indexes have a high correlation with each other, with values ranging from 0.818 to 0.998. However, the lowest correlations were found with N2AG with all the indexes, with Spearman correlation coefficients near to zero. This occurs because Z-scores normalize some values near to zero. Hence, when these indicators are aggregated using the geometric method, the high scores result into values near zero (low vulnerability). Besides, the correlation between N2AG and N4AG is negative, which indicates that the flood vulnerability values vary in contrast to each other.

All scenarios with linear aggregations have linear and positive correlations (Figure 3-4a–f). This is not the case for all correlations between the indexes based on geometric aggregation and the others (Figure 3-4g–o). Although N4AG (Figure 3-4m) has a high correlation with all the indexes that used linear aggregation, it is not linear.

The robustness of the results when considering the normalization and aggregation steps was also tested by computing the shift in rank for each census block (CB) (Figure 3-5 3-4). Overall, the vulnerability outcomes for each CB obtained by the different normalization and aggregation methods confirmed the flood vulnerability independence of the normalization scheme selection. On the other hand, flood vulnerability tends to be sensitive to the aggregation schemes.

CB1 and CB7 had, overall, the highest vulnerability scores (i.e., they were usually ranked with high vulnerability by all scenarios), with a relatively low sensitivity. This is mainly because these are the most urbanized areas, and hence, after normalization, they had the highest vulnerability scores, given their higher population density. CB11 was the census block with the highest variability, whereas CB12, CB19, CB13, CB3, and CB4 were the least sensitive ones. In Figure 3-5, the higher sensitivities are observed in all census blocks for the N2AG index. Similarly, N4AG presents relative differences in most of the census blocks in comparison to the other indexes. Indeed, the geometric aggregation method carries the most sensitive in the flood vulnerability outputs. Meanwhile, all normalization techniques with linear aggregation stayed almost in the same rank position, except when considering the distance to target normalization (N4AL) for the CB4.

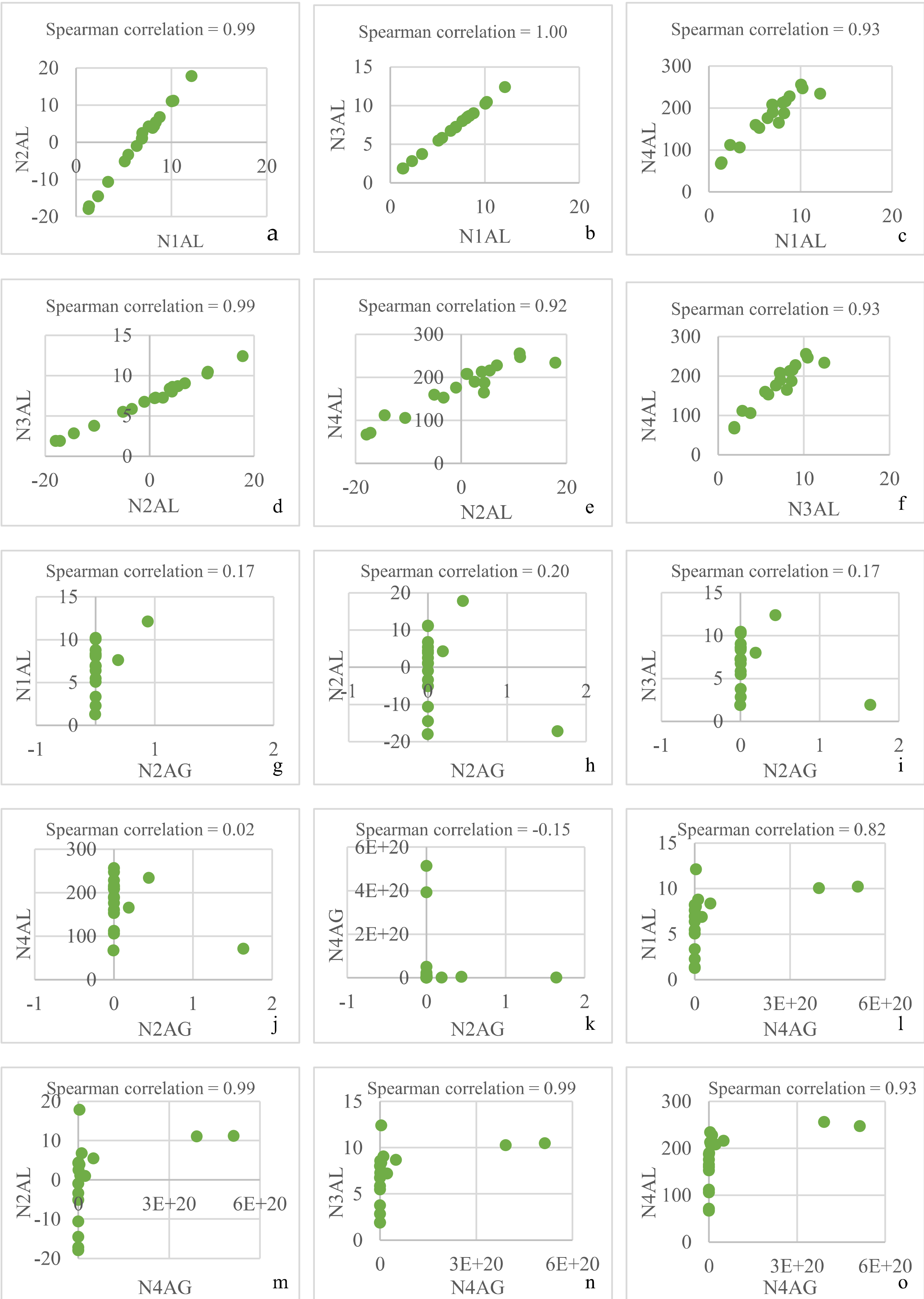

Figure 3-4 - Correlation between flood vulnerability indexes of normalization and aggregation methods. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

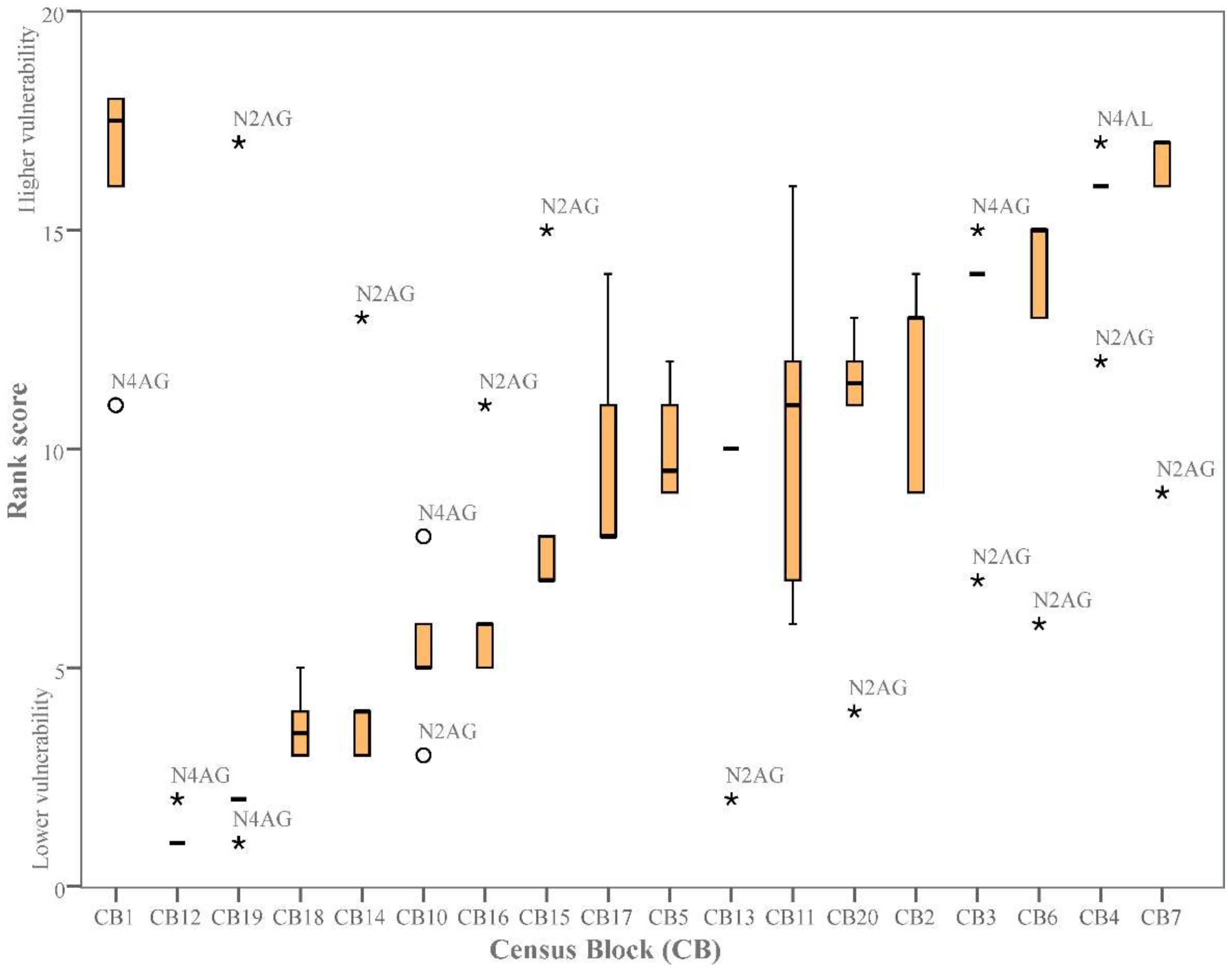

Figure 3-5 - Ranking by different normalization and aggregation methods. The census block's (CB) are organized according to their rank score values. High ranks indicate higher vulnerability whereas lower values represent CB ranked with low vulnerability. Outliers are denoted by circles and extremes by asterisks. The CB spatial location is shown in Fig. 1. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

To understand how these methods affect the spatial behavior of flood vulnerability, maps with the class switches were generated by using four classification methods. These maps were classified into "very low", "low", "medium", "high", and "very high" flood vulnerabilities (AROCA-JIMENEZ *et al.*, 2017; AROCA-JIMÉNEZ *et al.*, 2018; DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018) based on the natural breaks and equal interval classification methods (Figure 3-6) and quantile and standard deviation classification methods (Figure 3-7).

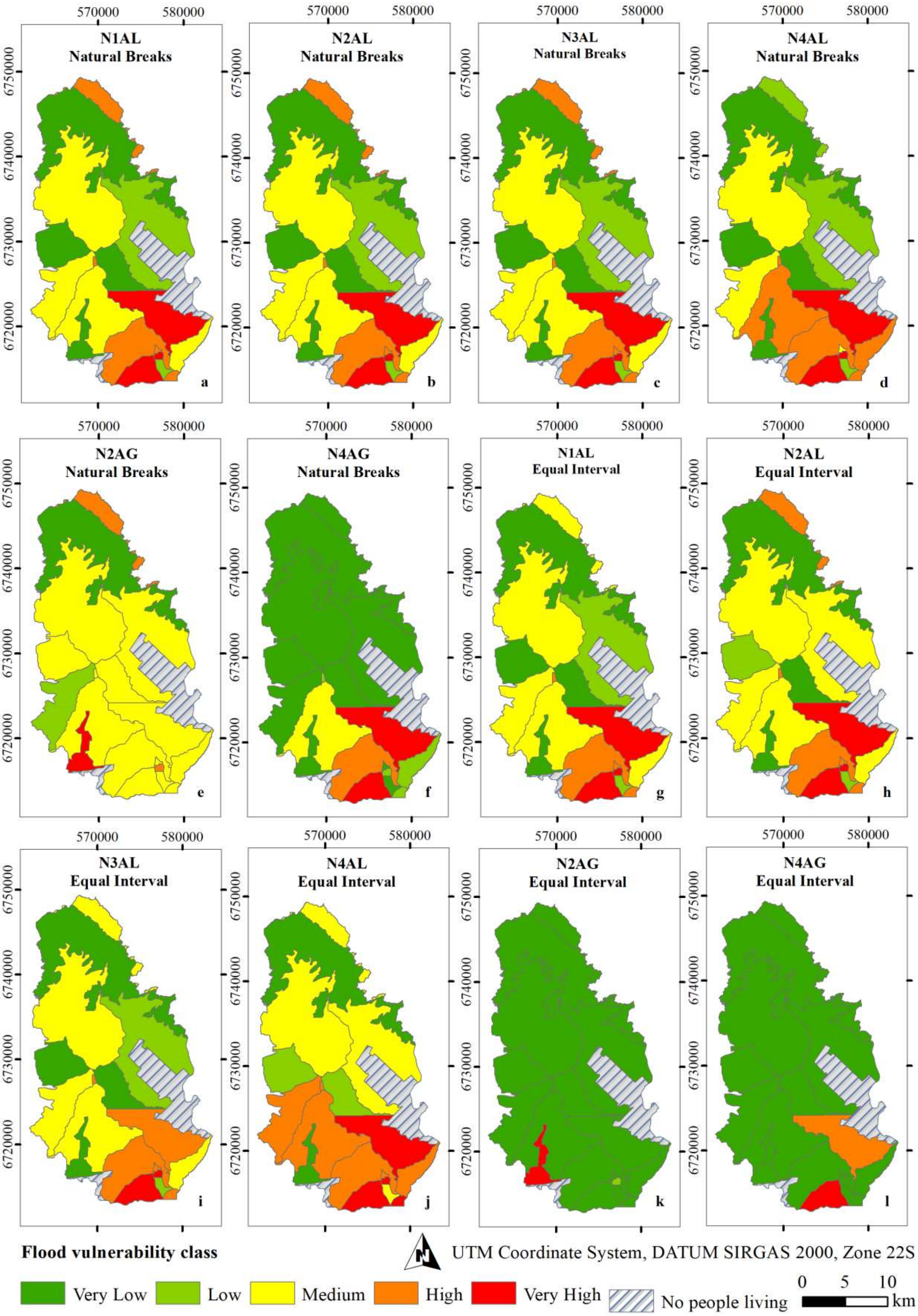

Figure 3-6 - Vulnerability class switches for different normalization and aggregation methods based on natural breaks and equal interval classification methods. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

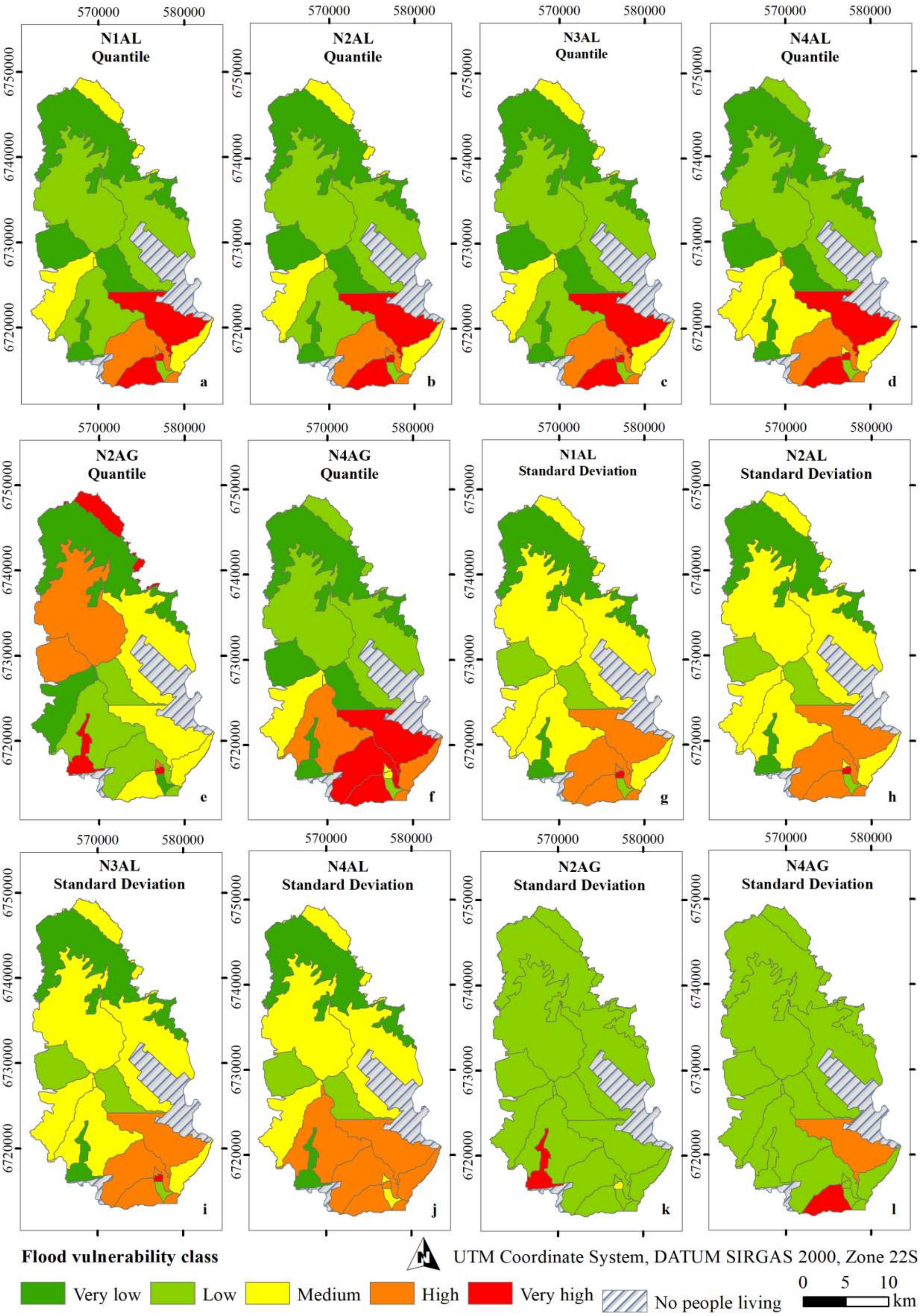

Figure 3-7 - Vulnerability class switches for different normalization and aggregation methods based on quantile and standard deviation classification methods. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

When considering the linear aggregation (AL), the spatial distributions of the vulnerability obtained by the Min-max (N1), z-scores (N2), and distance to target (N3) normalization methods are identical for all the census blocks for the natural breaks (Figure 3-6a–c), quantile (Figure 3-7a–c), and standard deviation (Figure 3-7g–i) classification methods. The only exception occurs when using the equal interval approach (Figure 3-6a,g,h) and the ranking normalization (N4).

The flood vulnerability classes generated by the geometric aggregation (AG) method are, in some cases, drastically different when compared with linear aggregation for all classification methods. Indeed, some census blocks change from the "very low" (Figure 3-6a–c) to "very high" (Figure 3-6e) vulnerability class. Such a high sensitivity from using different aggregation methods can result in inaccurate outputs. The major differences were observed in the equal interval (Figure 3-6k,l) and standard deviation (Figure 3-7k,l) classification methods, where most census blocks were classified with a "very low" and "low" vulnerability, according to the geometric aggregation method. This tends to underestimate the real vulnerability.

When fixing the index and focusing on the classes generated by different classification methods, significant differences can be found. For instance, for the N1AL index, one census block changed from the "high" to "medium" vulnerability class created by the natural breaks (Figure 3-6a) and equal interval (Figure 3-6g) methods, respectively. In comparison, in the same index, four census blocks changed their classes from the natural breaks (Figure 3-6a) to quantile (Figure 3-7a) classification method. These differences took place for all the indexes in all classification methods. Indeed, the index classification methods introduced great uncertainty.

Figure 3-8 demonstrates the percentage of the areas classified according to each index and classification method. The percentage of the census block for each class was similar, except for the standard deviation method, where the quantities of the census block in each class changed significantly in all the normalization and aggregation methods. For example, for the N1AL and N2AL indexes, 16.67% of the census block was classified as having "very high" vulnerability, which strongly disagrees with the standard deviation classification method, which calculated 5.56%.

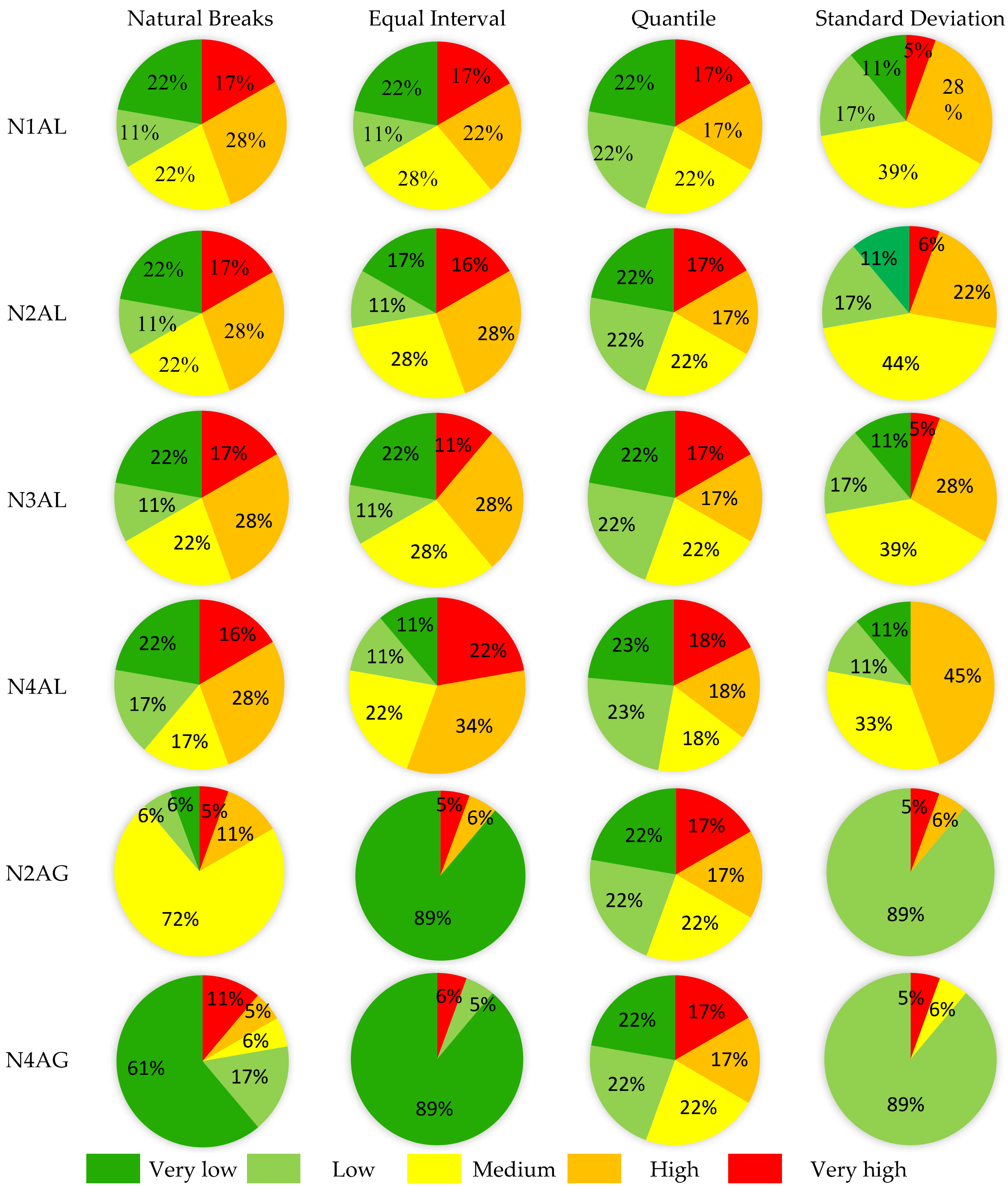

Figure 3-8 - Percentage of census block (n=18) for each vulnerability classes according to different normalization and aggregation methods. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

Other percentage differences took place in the same classification methods as the N4AL and aggregation methods when compared with the N1Al, N2Al, and N3AL indexes. It is important to note that all indexes have the same quantities for all classes in the quantile classification method. Although the percentage is the same, there are spatial changes (e.g., in the N1AL index, 22% of the census block was classified as having "medium" vulnerability in the natural breaks and quantile classification methods); when a census block was classified as having "medium" vulnerability for the N1AL index classified using natural breaks, the same blocks were classified as having "low" vulnerability for the N1AL index using the quantile method.

Finally, the performances of the classification methods were analyzed by the AIC estimations (Table 3-2), where the lowest values indicate the best performances. These estimations were not performed for the indexes based on z-scores normalization with linear (N2AL) and geometric aggregation (N2AG), because the sum of all the indicators was zero, and some indicators had negative values. Overall, the natural breaks method provides the lowest AIC for the N1AL and N3AL indexes; however, for the equal interval methods, we found the lowest AIC for N4AL and N4AG. As shown in Table 3-2, the geometric aggregation method (N4AG) also resulted in higher variances when compared to the other indexes that used linear aggregation.

Table 3-2 - Performance of classification methods for flood vulnerability indexes based on different normalizations and aggregation techniques. N1 = Min-max normalization; N2 = Z-scores normalization; N3 = distance to target normalization; N4 = ranking normalization; AL = linear aggregation; AG = geometric aggregation.

Classification Methods	N1AL	N3AL	N4AL	N4AG
Natural Breaks	296.89	314.03	7892.39	-13.98
Equal Interval	296.90	314.11	7886.24	-48.06
Quantile	297.04	314.33	7893.19	-5.92
Standard Deviation	297.07	314.26	7890.35	-29.60

3.4. Discussion

We verified the sensitivity of the different normalization and aggregation methods to construct a flood vulnerability index. Additionally, we investigated how different index classification methods could modify the flood vulnerability results. By analyzing the outputs, we could derive the following general summary: (i) most of the indexes have a high positive and linear correlation between each other, except for indexes generated with geometric aggregation, (ii) a high sensitivity to flood vulnerability arises from indexes created by geometric aggregation when compared with linear aggregation, (iii) the results are not sensitive to the different normalization methods, (iv) the flood vulnerability classes vary significantly for the indexes based on geometric aggregation for most classification methods, except quantile, (v) significant spatial changes of the flood vulnerability class occur for equal intervals for indexes that do not change outputs the for other classification methods, and (vi) according to the AIC, the natural breaks and equal intervals have the best performances among the investigated classification methods.

No significant differences were observed among the min-max, z-scores, and distance to target normalization methods with linear aggregation. The low sensitivity by normalization methods based on linear aggregation were also demonstrated by the shift in rank (Figure 3-5). Even though ranking normalization with liner aggregation brought a high Spearman's correlations coefficient (0.92 to 0.93), there were small spatial changes in the flood vulnerability class in comparison with the other normalization methods with linear aggregation. High Spearman's correlation coefficients (>0.98) for the min-max and z-scores were also found in the vulnerability indexes elaborated by other authors (NAZEER; BORK, 2019; YOON, D. K., 2012). However, for other application areas (e.g. agricultural sustainability index) significant differences were found according to different normalization methods (TALUKDER; HIPEL; VANLOON, 2017).

On the other hand, when flood vulnerability indexes were created by geometric aggregation, the outputs were very distinct. This is because indicators with very low values are fully compensated by indicators with high values (NARDO *et al.*, 2008). This can be observed in Figure 3-6 and Figure 3-7, where most of all parts of the Maquiné Basin were classified as "low" or "very low" flood vulnerabilities. Simultaneously, this method forbids to use indicators with zero scores or with normalization techniques that result in zero scores, such as the min-max. Since studies of vulnerability normally include social, economic, cultural, environmental, and other dimensions, these indicators are mutually preferentially independent. In these cases, linear aggregation is preferred (GAN *et al.*, 2017).

In addition to uncertainty regarding the aggregation method, we identified high uncertainties in the index classification. High spatial sensitivities were observed in all the classification methods. For the equal intervals, different from other methods, changes occurred with the N1AL, N2AL, and N3AL indexes. Since it divides the score data into equalsized classes, its performance might not be optimal for different types of normalization and aggregation methods whose distributions scores are different. The best performance confirmed with the AIC were attributed to natural breaks and equal intervals. Based on the disadvantages of the equal interval methods mentioned above and based on the AIC, the natural breaks method performed more efficiently than the others. Since the quantile method divides the data by the quantities of elements in each class, its performance might not be optimal for different distributions, and the standard methods do not show real scores, only how far these are from the average. On the other hand, the natural breaks method could show the variance of each class from the average and determine the location of class breaks based on the numerical scores of the features. These methods generated the most suitable classification map for other index studies as landslide susceptibility (BAEZA; LANTADA; AMORIM, 2016), and intelligent compaction data (MAZARI *et al.*, 2017).

The spatial analysis of the elaborated indexes showed that some regions tend to be overly sensitive to model changes, whereas others present robust outcomes (e.g., CB12, CB19, CB13, CB3, and CB4 in Figure 3-5). Furthermore, the vulnerability classification into different classes also contributed to the spatial variation. This information can be used by end users to conduct further studies aiming to investigate the role of the different criteria in shaping the vulnerability outcomes.

Notwithstanding the advances of our study, the limitations should be also pointed out. Although the investigated methods are most commonly used in flood vulnerability studies, there are others, such as the categorical scale, binary standardization, division by total and fuzzy for normalization methods, and non-compensatory aggregation technique. Therefore, future studies should focus on understanding the uncertainty underpinning these methods. Likewise, the choice of the criteria and the variation of their weights also generate significant uncertainty (DE BRITO; ALMORADIE; EVERS, 2019; DE BRITO; EVERS; HÖLLERMANN, 2017) and should be the subject of future research. Here, we decided to use equal weights because of difficulties in finding an acceptable weighting scheme. Nevertheless, when information on the indicator's importance is available, weighted indexes are recommended.

3.5. Conclusions

The present study investigated the effects of the use of different normalization, aggregation, and classification methods in order to construct a flood vulnerability index. The sensitivity analysis results provided information on the regions with high sensitivity, as well as the techniques that increased this variability. Overall, we concluded that:

- Normalization techniques such as the min-max, z-scores, and distance to target do not make significant changes in the flood vulnerability outputs. Among the normalization methods, the ranking method was most sensitive.
- The choice of aggregation method strongly affects the vulnerability outcomes. For our case study, the geometric aggregation method was more sensitive when compared with linear aggregation, as it offered inferior compensability for the indexes, with lower scores.
- For each classification method (natural breaks, equal interval, quantile, and standard deviation), there were changes in the same census block with respect to over- and underestimating the flood vulnerability. However, the natural breaks method had the best performance, according to the AIC values.

The present study contributes to addressing the importance of measuring the sensitivity of different steps while building vulnerability indexes. Based on our results, efforts can be taken to reduce the uncertainty. Focus should be given to census blocks classified with high and very high vulnerability and high sensitivity. These blocks are potentially vulnerable but need to be further examined due to their degree of uncertainty. Hence, the outcomes can support end users in reducing uncertainty and improving decision-making. The proposed approach can be transferred to other case studies, providing insights regarding the sensitivity of the flood vulnerability indexes.

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CHAPTER 4

Sensitivity analysis of criteria weights for the construction of flood vulnerability indexes: a participatory approach

This section is based on the following manuscript in progress of submission

MOREIRA, L.L.; de BRITO, M.M.; VANELI, F. M.; KOBIYAMA, M. Sensitivity analysis of criteria weights for the construction of flood vulnerability indexes: a participatory approach, 2022.

Abstract: The assessment of flood vulnerability involves a wide range of uncertainties. To better understand the variability of vulnerability index outcomes according to different input parameters, sensitivity analyses are needed. In this study, we conducted a sensitivity analysis of the indicators' weights used to construct flood vulnerability indexes in the Maquiné Basin - Brazil. We explored changes in vulnerability scores using weights derived from a participatory survey with 44 stakeholders and by comparing with an equal weighting scheme. Results helped us identify areas with low and high uncertainty and the variables that contribute to this. By adopting a participatory approach, it was possible to consider multiple stakeholders' views. Overall, the preference of the indicators' weights did not significantly differ among distinct socioeconomic characteristics of stakeholders; also, the stakeholders' choice of weights had little effect on flood vulnerability results. In comparison to equal weights, the flood vulnerability outcomes were similar, which indicates that the results were robuts and not highly sensitive to criteria weights. The advantages of the proposed participatory sensitivity analysis include a higher acceptance of the results by the involved stakeholders. The methodology applied is straightforward and may be easily adapted to other multi-criteria decision making problems.

Keywords: composite indicators; flood vulnerability; weighting; sensitivity analysis

4.1. Introduction

Vulnerability assessments are essential to understand the multiple variables that increase or decrease the likelihood that exposed elements will be negatively affected by floods (Birkmann *et al.*, 2013a). These assessments can increase our knowledge of flood risk and provide a starting point for determining effective means to reduce flood impacts

(KELLY; ADGER, 2000; MOREIRA; DE BRITO; KOBIYAMA, 2021b). In this context, vulnerability maps are fundamental for planning and responding to flood disasters (NIGUSSE; ADHANOM, 2019; MOREIRA; DE BRITO; KOBIYAMA, 2021b)

Among the methods used to analyze flood vulnerability, index-based approaches are the most used ones as they allow to holistically evaluate the vulnerability by considering its different dimensions (BALICA *et al.*, 2013; BIRKMANN *et al.*, 2013a; NASIRI *et al.*, 2016). Indexes have been regarded as particularly helpful in vulnerability assessment as they can combine different types of data at different scales. However, each step of the index construction introduces uncertainty as researchers are faced with several choices between plausible alternatives (TATE, 2012). Indeed, steps such as the selection of indicators and their normalization, aggregation, weighting and classification have been shown to greatly influence index outcomes (MOREIRA; DE BRITO; KOBIYAMA, 2021a). Among these steps, weighting is deemed as the main contributor of uncertainty (BECKER *et al.*, 2017; CHEN *et al.*, 2013; de BRITO *et al.*, 2019; ROGELIS *et al.*, 2016). Even small changes in weights may significantly impact index results, leading to the over-or under-estimation of flood vulnerability and consequent inaccurate outcomes (FEIZIZADEH; BLASCHKE, 2014).

Even though each indicator contributes differently towards flood vulnerability, most existing indexes employ an equal weighting, i.e. all indicators are given the same weight (FEKETE, 2012). According to Tate (2012), equal weights are used as a default option given the lack of understanding of the relationship between indicators. Despite the growing interest in vulnerability assessments (MOREIRA; DE BRITO; KOBIYAMA, 2021b), meta-analytical syntheses of the variables contributing to vulnerability are largely missing, and the existing ones are inconclusive (BAMBERG *et al.*, 2020). Hence, there are no clear standards on which variables should be considered and how important they are for assessing vulnerability. However, even though it is challenging to find an acceptable weighting scheme, an unweighted index is still subjective rather than objective, as they imply that all indicators are “worth” the same (OULAHEN *et al.*, 2015; WANG *et al.*, 2009). In most cases, the scientists conducting the study define the weights without clearly explaining the rationale used. This hinders the study's replicability as indicator weights vary depending on each person’s opinion and experience (de BRITO *et al.*, 2017b).

Overall, the attribution of indicator weights can be done by following a: (i) equal weighting approach - considering the same importance for all indicators (HERNÁNDEZ-URIBE *et al*., 2017); (ii) statistical approach – using methods such as Principal component analysis (PCA) (GU *et al*., 2018); (iii) participatory approach - by soliciting expert *(SHAH et al*., 2018) or public opinion (SCHUSTER-WALLACE *et al*., 2018), and (iv) multi-criteria decision-making (MCDM) – using tools such as the analytical hierarch process (de BRITO *et al*., 2018).

In recent years, participatory approaches that rely on expert knowledge have been widely employed to address the subjectivity in defining indicator weights (de BRITO *et al*., 2019; EKMEKCIOĞLU *et al*., 2021; KANANI-SADAT *et al*., 2019). They support the exploration of complexities and uncertainties by creating multiple scenarios according to different stakeholders' opinions (KOWALSKI *et al.,* 2009). The hypothesis is that if several practitioners or affected citizens with expertise in vulnerability analyses are involved in creating an index that they find helpful, more robust outcomes will be reached. Furthermore, they are likely to incorporate the index outcomes into policy decisions (OULAHEN *et al*., 2015).

Within this context, several studies demonstrated that the active participation of stakeholders in the research design can lead to (i) a sense of the multiplicity of perspectives producing shared understandings; (ii) an ability to transform implicit and tacit knowledge into useful information for decision and policy-making; (iii) an enhanced credibility and deployment of the final results; and (iv) an increased social learning among participants (de BRITO *et al*., 2018; EVERS *et al*., 2018; LOPES; VIDEIRA, 2018; MAVROMMATI *et al*., 2017; SAARIKOSKI *et al*., 2019). Truly collaborative research, which promotes active learning and coproduction, can play an important role in supporting integrative flood risk management (VAN HERK *et al*., 2011). Furthermore, participation can provide a transparent way of building indicators by systematically showing underlying assumptions. However, stakeholder participation does not necessarily eliminate the subjectivity involved in weighting indicators (CHEN *et al*., 2013; de BRITO *et al*., 2019). Stakeholders have diverse backgrounds, experiences, and worldviews that influence their understanding and, consequently, the importance they attribute to different indicators (SLATER; ROBINSON, 2020). According to Akter and Simonovic (2005) this subjectivity is due to the fuzzy nature of human thought, where uncertainty plays a major role when a large number of stakeholders with diversified opinions are considered.

Hence, to better understand the uncertainties involved in building indexes and ascertain their robustness, sensitivity analyses applied to the weighting of indicators are essential (ABEBE *et al.*, 2018). Despite their importance, uncertainty and sensitivity analyses remain scarce in the context of flood vulnerability assessment, with few applications (e.g. FEIZIZADEH; KIENBERGER, 2017, DE BRITO *et al.*, 2019). As such, index uncertainties are often ignored.

The aim of this study is, therefore, to evaluate the sensitivity of flood vulnerability indexes by considering different weighting schemes derived in a participatory approach. For it, we address the following questions: (i) which indicators are more relevant for assessing flood vulnerability in the study area according to stakeholders? (ii) Are there differences or similarities in the weights derived by different stakeholders? (iii) Does the choice of weight significantly affect the outputs of flood vulnerability assessment? (iv) How does the vulnerability scores vary in space according to different weights? (v) Are there significant changes in spatial outputs of flood vulnerability when using equal weights or attributing relative importance to indicators through a participatory approach? We discuss these questions by carrying out the case study of the Maquiné river basin, located in the South of Brazil.

4.2. Material and methods

4.2.1. Study area

This study was conducted in the Maquiné river basin (510 km²), located in Rio Grande do Sul state in southern Brazil (Figure 4-1). The area presents a typical mountain landscape with altitudes ranging from 1 to 975 meters. The climate is mostly humid subtropical, with a mean annual rainfall between 1700 and 2109 mm. The basin land use is covered by forest (78.3%), crops (11.7%), bare soil (5.5%), reforestation areas (3.0%), water (0.9%), and urban areas (0.7%). Floods occur annually in the region, affecting houses and displacing people. For example, in May 2008 a severe flood event occurred, and the river flow, which has an average flow of 15.2 m³/s, raised to 568 m³/s (de CASTRO; Mello, 2013).

Most of Maquiné' river basin inhabitants (~70% of 6,024 people) live in rural areas (IBGE, 2010). The basin is divided into twenty census blocks (CB), which correspond to the smallest territorial administrative unit in Brazil. The urban area is located in CB 1, south of the basin, and the CBs 8 and 9 were removed from our analyses since no persons live there.

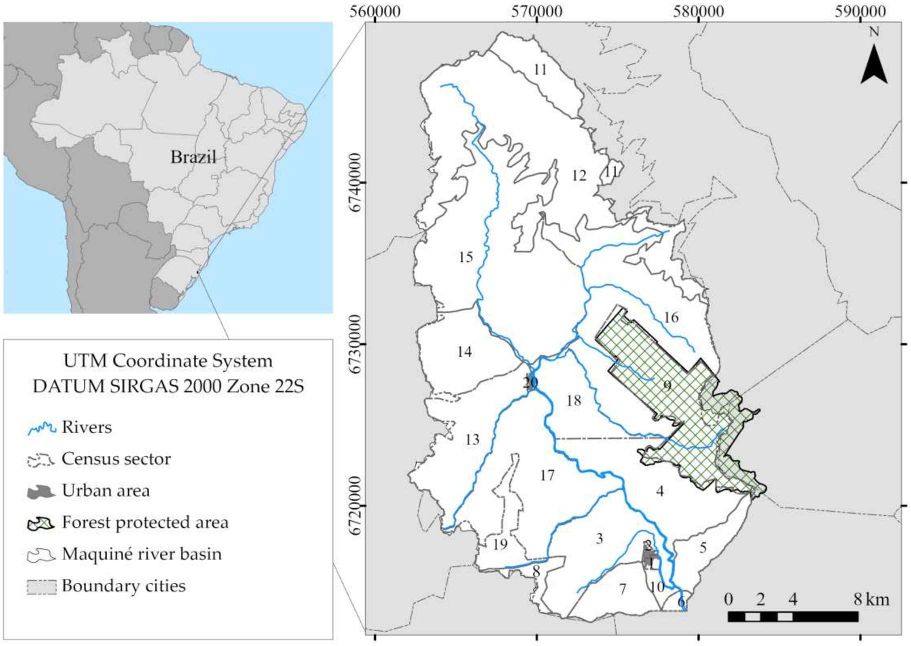

Figure 4-1- Location of Maquiné river basin and census blocks (CB) within the basin. The CBs 8 and 9 are inhabited.

4.2.2. Selection and normalization of vulnerability indicators

The construction of an index usually involves the following steps: (i) identification of the phenomenon to be measured; (ii) indicator's selection; (iii) indicator's normalization; (iv) indicator's weighting; (v) indicator's aggregation; (vi) classification of the results in classes; (vii) sensitivity and uncertainty analysis; and (viii) validation (MOREIRA; DE BRITO; KOBIYAMA, 2021b; NARDO *et al.*, 2008).

In this study, we selected 13 indicators to assess the flood vulnerability in the Maquiné river basin (Figure 4-2). This selection was based on: (i) the indicators' relevance evidenced by a systematic literature review (MOREIRA; DE BRITO; KOBIYAMA, 2021b), (ii) their availability of data, and (iii) the indicators' suitability to the case study context. A detailed description of the reasoning for indicator selection is provided in a previous paper by the authors (see MOREIRA; DE BRITO; KOBIYAMA, 2021b). These indicators were grouped into social, economic, and physical vulnerability categories. The data used to represent them were obtained from the Brazilian 2010 Census (IBGE, 2010) and were normalized by using the min-max method (Equation 1). Since the "per capita income" indicator reduces vulnerability, it was normalized inversely. This was done by multiplying the "per capita income" indicator by minus one and then adding their minimum value. This results in a dataset where high values increase the vulnerability while low ones correspond to a decreased vulnerability.

$$y_{in} = \frac{x_{in} - \min(x_{in})}{\max(x_{in}) - \min(x_{in})} \tag{1}$$

where y_{in} is the normalized indicator; and x_{in} is the indicator value.

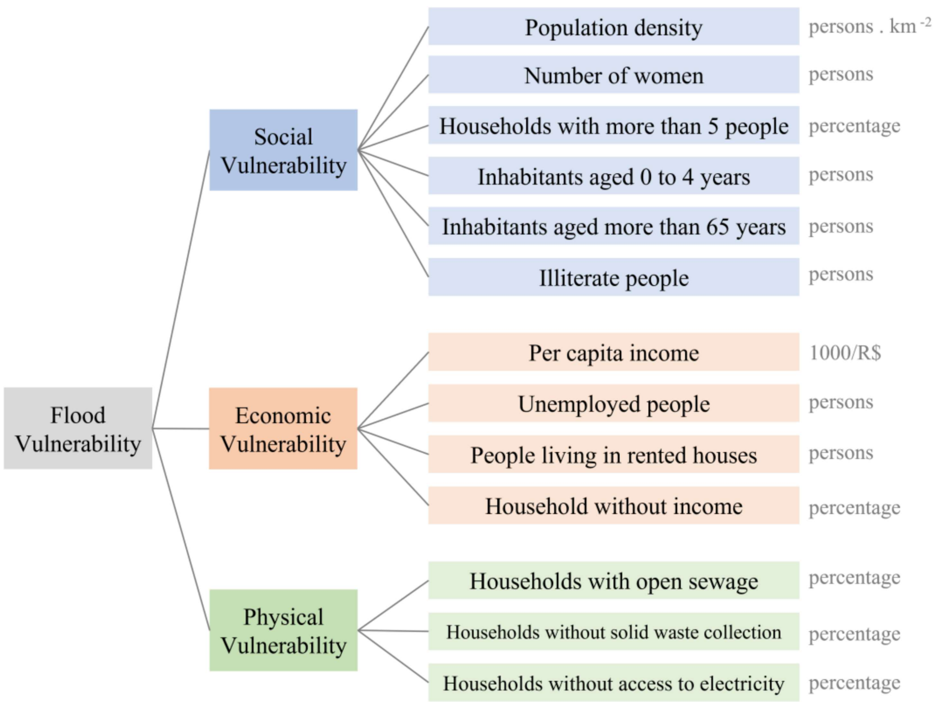

Figure 4-2 - Input flood vulnerability indicators organized hierarchically. The units used to measure each indicator are indicated in grey.

4.2.3. Participatory weighting of indicator's weights

We investigated the sensitivity of the vulnerability index by employing different indicators' weights obtained through a participatory survey. The survey was created on the Survio platform (Appendix A) and shared with stakeholders who (i) have knowledge on flood vulnerability analysis, acquired through experience or education and/or, (ii) who know the study area (i.e. by living in risk-prone areas or by conducting research there). A total of 300 stakeholders identified via snowball sampling were invited to participate in our study.

The survey was used to estimate preferences around the relative importance of each indicator. It was divided into three parts: (i) general information about the stakeholders, including knowledge of flood vulnerability, knowledge of the study area, age, professional sector (e.g. governmental organizations, universities, private companies, academic, other), and education degree; (ii) weights attributed to social, economic, and physical indicators; and (iii) open questions about suggestions of other relevant vulnerability indicators to include and other recommendations.

The participants attributed weights by using the 'point allocation' approach, first across criteria main categories (economic, social and physical in Figure 4-2) and, second, across criteria within each category. This method was chosen given its simplicity and easiness of implementation in online surveys (ESANGBEDO *et al.*, 2021). For example, for social vulnerability (Figure 4-2), the participants were asked to give weights to six indicators on a scale from 0 to 100, for which the total sum was not higher than 100%. To obtain the global weights for each indicator, we normalized the local weight values according to the weights given to each category.

4.2.4. Aggregation and sensitivity analysis of indicators' weights

In order to generate the flood vulnerability maps, the normalized indicators were multiplied by the participatory weights obtained and subsequently summed (Equation 2). The results were then classified into different vulnerability classes: "very low", "low", "medium", "high", and "very high", by considering the natural breaks methods. These choices were made because they presented a better performance than other normalization, aggregation and classification techniques, as shown by Moreira *et al.* (2021a).

$$\mathrm{Index} = \sum_{i=1}^{q} w_i I_i \tag{2}$$

where $\sum_{i}^{n} w_i = 1$ and $0 \leq w_i \leq 1$, for all $i = 1, \ldots, n$

where w is the weight associated with a normalized value (I) for the indicator i; and q is the number of indicators.

To analyse the index's sensitivity according to the different weights given by stakeholders, we computed a vulnerability index for each participant. We then calculated the mean and standard deviation of the indexes' values. This allowed us to identify and visualize areas with high variability (i.e. CBs which present greater sensitivity in flood vulnerability outcomes). The scenario with the mean weighting was also compared to an index developed using equal weighting.

4.2.5. Statistical analysis of survey results

We performed a statistical analysis of the survey results using the software SPSS® (version 18.0.3). This allowed us to understand if there were significant differences in the weights derived by the stakeholders. We applied the Shapiro-Wilk test to examine if the weights were normally distributed in the sample. If the sample had a non-normal distribution, we used the Kruskal-Wallis test to analyze the indicator's weights according to the socioeconomic characteristics of the participants. In both tests, the confidence interval was set to 95%.

4.3. Results

A total of 44 persons replied to our survey (response rate of 14.7%). Most participants had a PhD degree, did not know Marquiné river basin, and had reasonable knowledge in flood vulnerability assessment. The mean age of the respondents was 26 to 40 years old (Table 4-1).

With regard to the weights given to each vulnerability category, the social was the most important one with a mean weight of 35.9%, followed by economic and physical with 34.7% and 29.4%, respectively (Figure 4-3). Within each category, local weights defined the importance of a single indicator (Figure 4-4). For example, households with open sewage received the highest importance (37.5% out of 100%) over the other two in the physical category. Similarly, within the social category, population density was rated the most important (24.8%), while the number of women was deemed as the least important criteria (8.7%).

Table 4-1. Survey participant's characteristics.

Characteristic	n	%
Level of knowledge in flood vulnerability assessment		
Low	7	15.9
Reasonable	20	45.5
High	17	38.6
Age		
Less than 25 years old	3	6.8
Between 26 to 40 years old	20	45.5
Between 41 to 65 years old	19	43.2
More than 65 years old	0	0.0
Level of education		
Elementary school	0	0.0
High school	0	0.0
Vocational school	0	0.0
Graduate	3	6.8
Specialization	4	9.1
Master's degree	13	29.5
PhD	24	54.5
If knows Maquiné river basin		
Yes, I live in Maquiné	3	6.8
Yes, I visited one or few times	2	4.5
Yes, visit periodically	7	15.9
No	32	72.7

We also computed the global weights by multiplying each indicator's local weight with its corresponding vulnerability category's relative weight. For example, unemployed people, belonging to the economic vulnerability category, had a mean global weight of 8.7%, as result of a product of 25.1% (local weight) and 34.7% (vulnerability category's relative weight). When considering the global weights, we noticed that per capita income had the highest importance (12.3%) followed by households with open sewage (11.0%) and households without solid waste collection (10.0%).

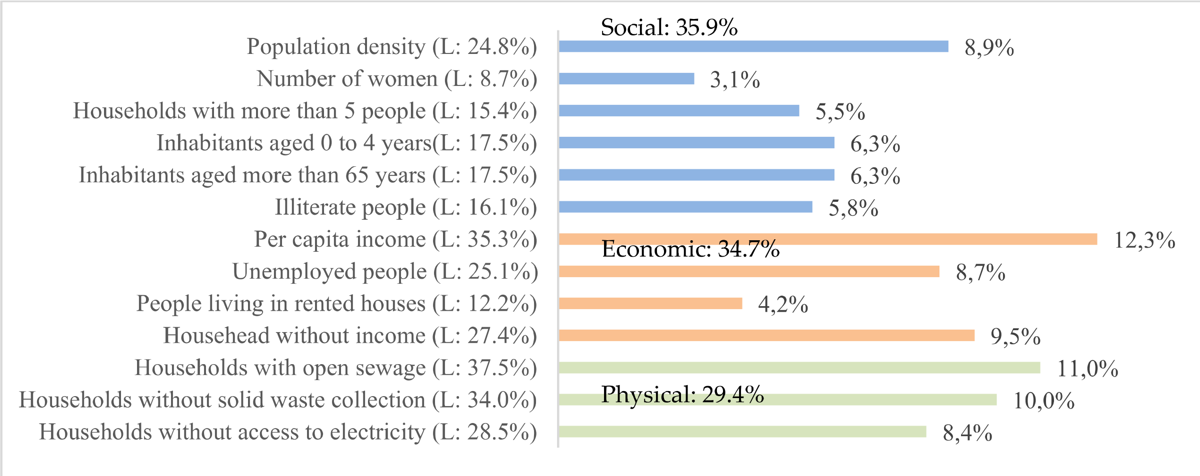

Figure 4-3 - Global (indicator importance considering the social, economic, and physical categories) and local (indicator importance within each category) weights of indicators. "L" denotes local weight. The colour blue represents the social vulnerability category, orange the economic, and green the physical.

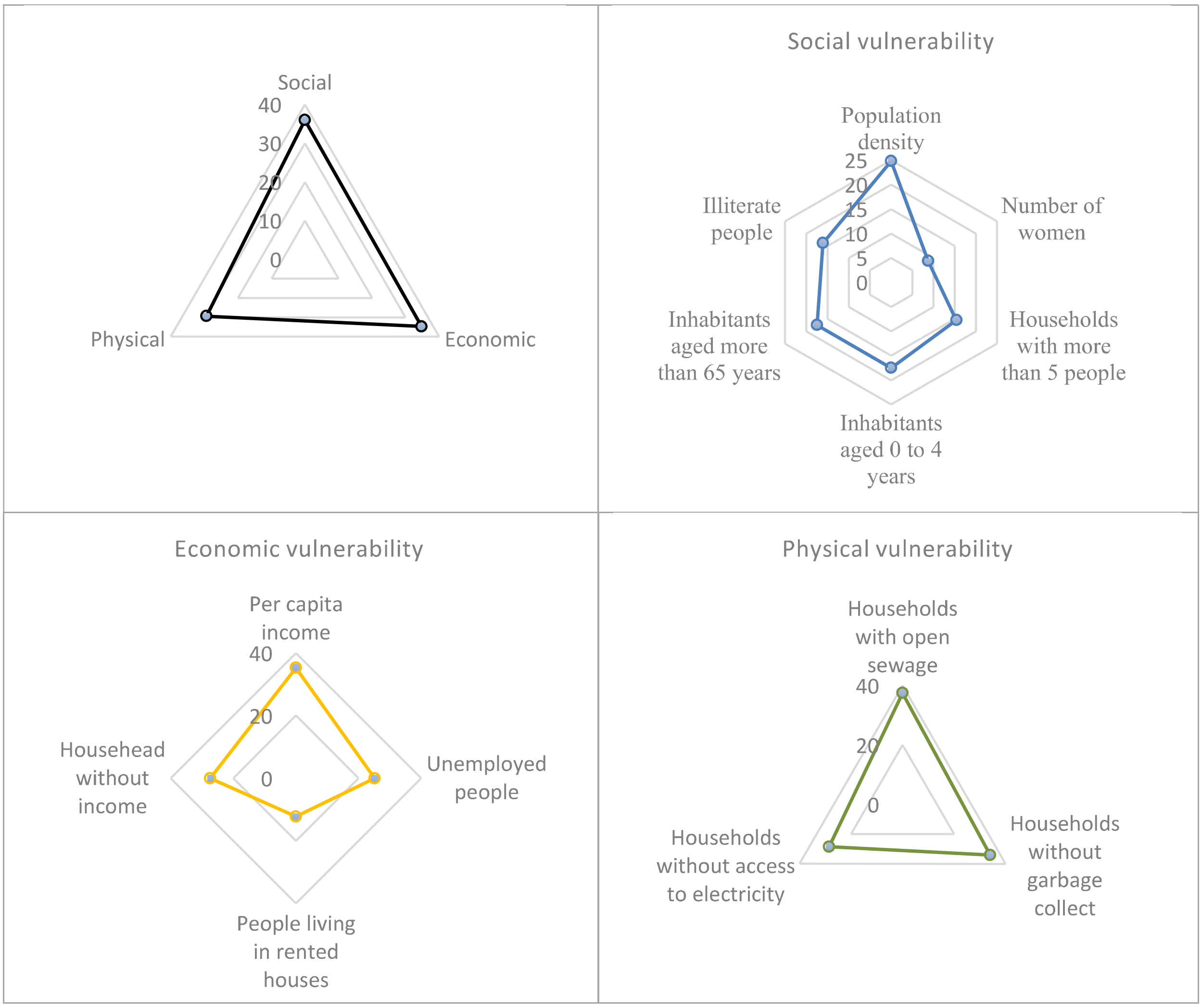

Figure 4-4 - Local weights mean and their standard deviation according to the 44 survey participants.

Based on the individual weighting schemes, we created vulnerability maps for each of the 44 stakeholders. Figure 4-5a shows the mean vulnerability results obtained by averaging the spatial outcomes of the individual maps, whereas Figure 4-5b shows their standard deviation. Overall, the mean vulnerability varied from 7.4 to 58.9. The results were then classified into "very low", "low", "medium", "high", and "very high" using the natural breaks method. Census blocks 1, 4, and 7 in the south had overall the highest vulnerability scores, classified were very high vulnerability. This is mainly because they are the most populated CB, encompassing 38.9% of the population in the Maquiné river basin. In contrast, census blocks 12, 14, 18, and 19 were classified as "very low" flood vulnerability. Such results are linked to the population density as these CBs encompass 3.4% of the total population in the basin.

In terms of standard deviation, census blocks 1, 4, 7 and 11 had the highest variability. The census blocks 1 and 4 are populated. The 11 one has the greatest number of households without garbage collection (90%) in the Maquiné basin. These indicators got highs global weights by the stakeholders.

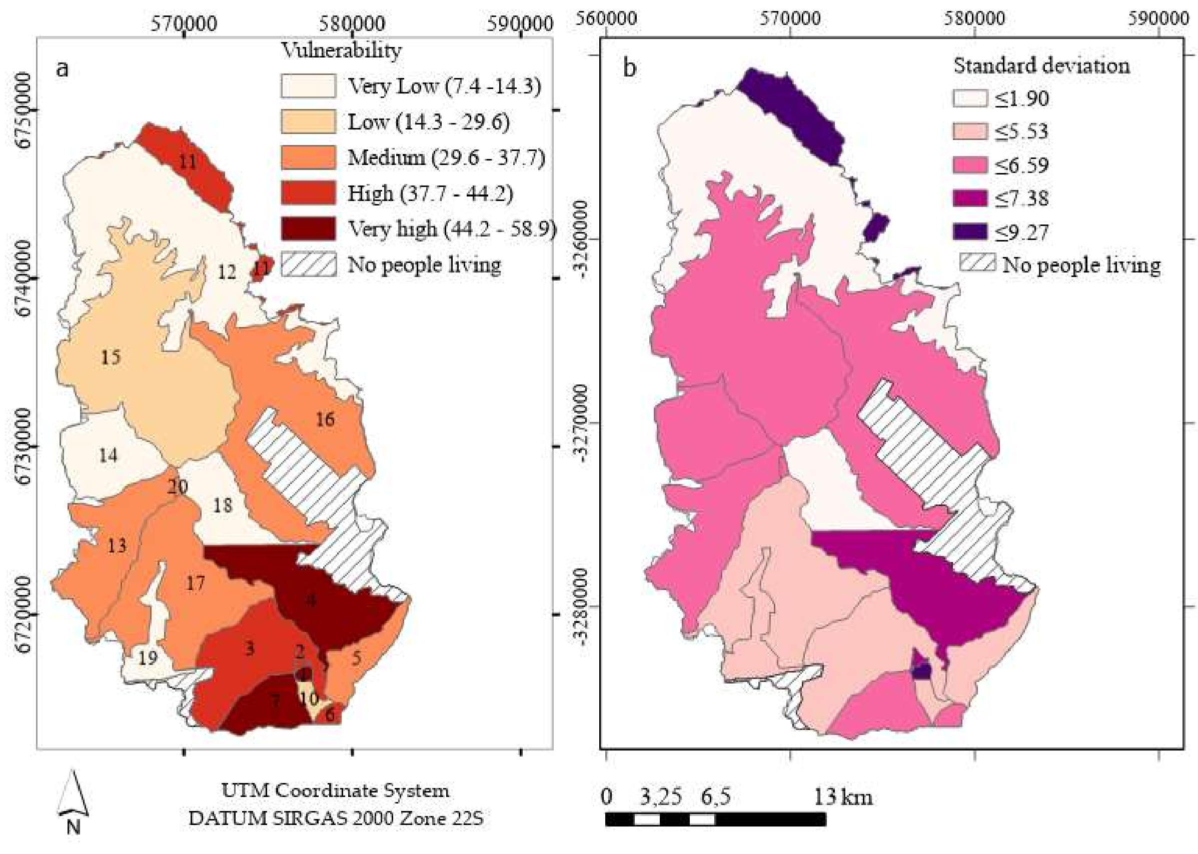

Figure 4-5 – Final vulnerability maps: (a) mean vulnerability obtained by averaging the results of each individual vulnerability map; and (b) standard deviation of the vulnerability maps by each stakeholder.

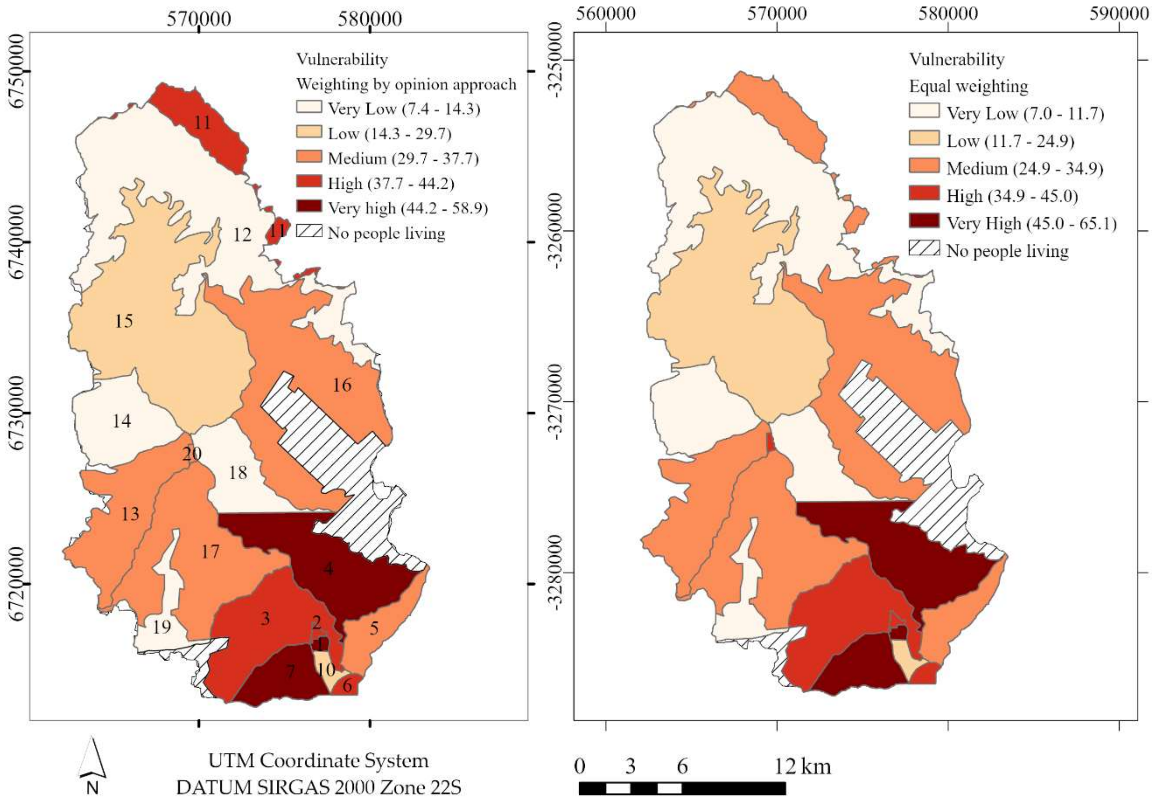

Figure 4-6 – Comparison of vulnerability map obtained by (a) using the mean local weights shown in Figure 4.3, (b) by considering an equal weighting.

In most census blocks, the flood vulnerability classes generated with weights by the stakeholders are similar when compared with equal weights (Figure 4-6). It indicates a low sensitivity on using relative importance to indicators. Indeed, the census blocks 11 change from "high" to "media" vulnerability class and census 20 change from "media" to "high".

In general, the indicators' weights presented non-normal distribution (Supplementary Table 4-2). The Kruskal-Wallis test demonstrated that the population mean ranks of weights of indicators did not significantly differ among different socioeconomic characteristics of stakeholders. To further investigate the similarities in the weights given by the stakeholders to the 3 vulnerability category we conducted a cluster analysis. Overall, there were no significant differences according to the participants age, level of education, level of knowlegd in flood vulnerability assessment, work sector, and if knows Maquiné river basin (Figure 4-7).

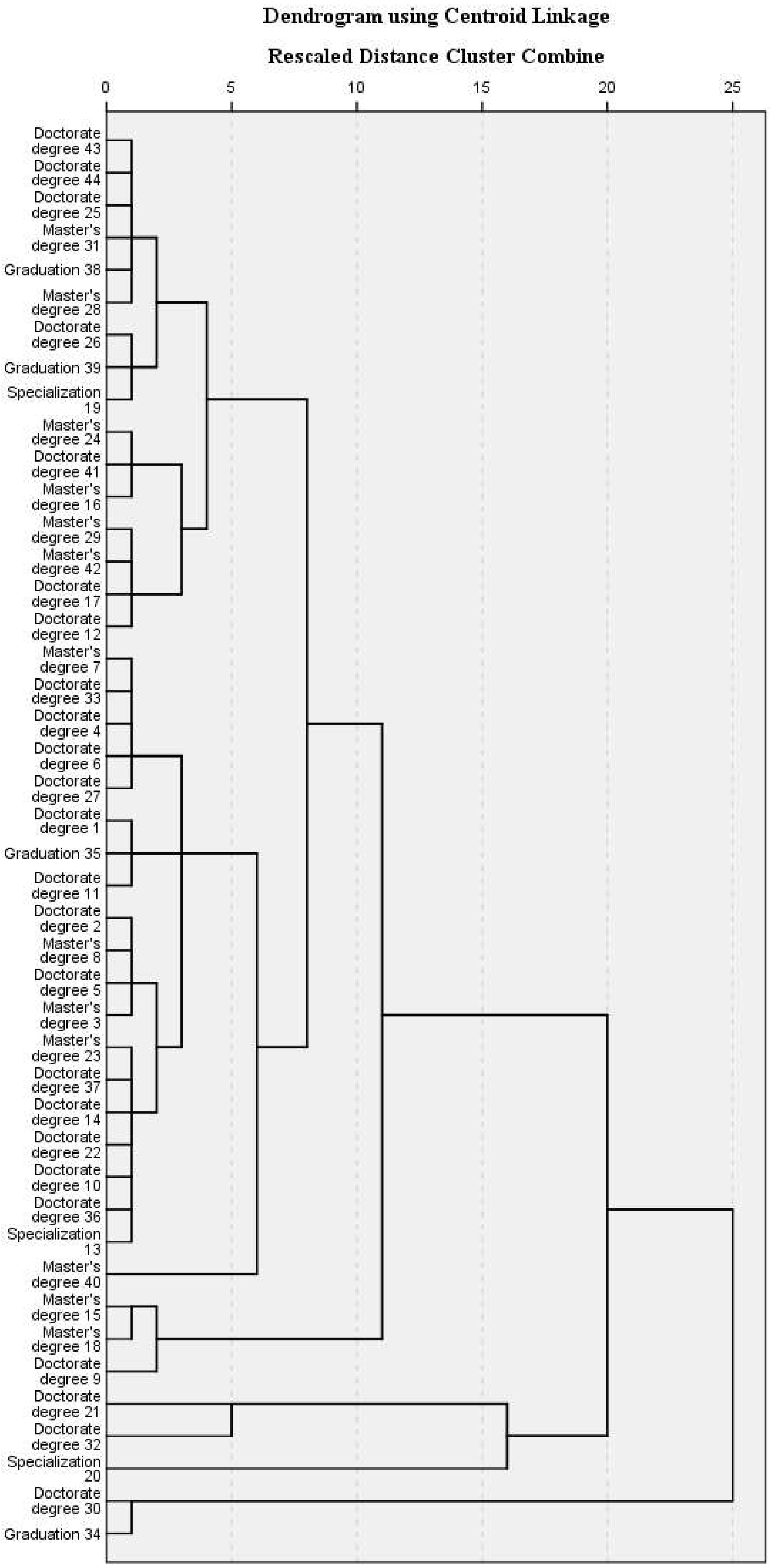

Figure 4-7 - Cluster analysis of social, economic, and physical categories considering the weights indicated by each participant. The numbers on the x-axis indicate the stakeholder identification.

4.4. Discussion

In this study, we investigated the sensitivity of flood vulnerability assessments according to different indicator's weights . From the outputs, we can derive the following general summary: (i) the weight choices are not dependent on the socioeconomic characteristics of the stakeholders. They rather depend on their individual opinions and personal experience; (ii) the weights choice of by different people has a significant effect on flood vulnerability quantification in some of the investigated areas; and (iii) the mean results are not sensitive to different weights of indicators when compared with equal weighting.

With regard to the indicator weights (question i), we found that similar to other flood vulnerability studies (DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018; SCHUSTER-WALLACE; MURRAY; MCBEAN, 2018; SHAH *et al.*, 2018), the per capita income was the most important variable for flood vulnerability assessment. However, other studies that applied the expert and public opinion to attribute weights in indicators, as "poor/improper building material" of a study in Pakistan (SHAH *et al.*, 2018) and in Brazil (DE BRITO; EVERS; DELOS SANTOS ALMORADIE, 2018), as "persons aged over 64 years living alone" of a study in Canada (SCHUSTER-WALLACE; MURRAY; MCBEAN, 2018). The relative importance to indicators reflecting financial conditions associated with high flood vulnerability in Brazil and Pakistan, countries in developing can be attributed to the social and economic reality, different to other countries like Canada, where the elder population living alone is most significant. In contrast, the less important weight attribute to gender, although the variable is one of the most used indicators, is present in 28.4% of studies on review literature to assess flood vulnerability using indexes (MOREIRA; DE BRITO; KOBIYAMA, 2021b). This indicator makes more sense in various countries except Brazil.

In the present study, the socioeconomic characteristics of stakeholders were not the main influence on the indicators' weights (question ii). This is similar to the findings by de Brito (2017). The previous experiences and perspectives of the stakeholders resulted in differences in the weighting of indicators. Hence, in the face of the complexity of flood vulnerability, different actors participating in the index construction can minimize the siloed views.

Concerning the question (iii), we found that despite the relative robustness, the vulnerability outcomes are locally sensitive to weight changes, especially in the 1 and 11 CBs. The largest uncertainties were found in regions where a significant percentage of an indicator with a high weight was assigned, for example, in census sector 11, about 90% of houses do not have garbage collection and this was considered one of the most relevant indicators in the study, even though this sector accounts for 1% of the basin's population. The other major uncertainties are located in regions with high population rates.

Despite the advances of the present study, some limitations need to be considered. The first refers to the lack of validation against independent data. As shown in a review by Moreira; De Brito; Kobiyama (2021b), less than 14% of flood vulnerability studies performed any form of validation. This limitation is associated with the difficulty of conducting experimental studies with vulnerability; the characteristics holistic, generic, and multidimensional of vulnerability; and the difficulty to estimate vulnerability for methodological reasons (FEKETE, 2009). For our study area, no impact data exists….. A second limitation concerns…

4.5. Conclusions

By using Maquiné river basin as case study, the present study investigated the effects of weighting in order to construct a flood vulnerability index. Overall, we conclude that:

- the preference of weights to indicators did not significantly differ among different socioeconomic characteristics of stakeholders;
- the choice of weights by different people had small effect on flood vulnerability results;
- the use of equal weights and choice of weights across people did not prove major changes in flood vulnerability outcomes.

The present study contributes to focus on the importance of assessing the sensitivity of different criteria weights. Although the difference is low, it is important to check them for each case study before choosing the method for construction of flood vulnerability index. However, it is important to note that care must be taken when making generalizations from the results obtained with this study, as they may vary for different areas of study or even for different samples in the same area of study.

The methodology used in this study for uncertainty analysis is straightforward and can be easily replicated in other studies. As observed by Moreira; De Brito; Kobiyama (2021b), only about 3.2% of 95 articles carried out uncertainty analyses to build flood vulnerability indices. Therefore, this simple participatory sensitivity analysis proposed here is recommended.

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Appendix

Table 4-2 - Shapiro-Wilk normality test for examining the distribution of the weights in the sample of each indicator.

	Indicator	Shapiro-Wilk test	
		p-value	**Distribution**
Economic	Per capita income	0.001	non-normal distribution
	Unemployed people	0.198	normal distribution
	People living in rented houses	0.000	non-normal distribution
	Househead without income	0.296	normal distribution
Social	Populational density	0.000	non-normal distribution
	Number of women	0.000	non-normal distribution
	Households with more than 5 people	0.030	non-normal distribution
	Inhabitants aged 0 to 4 years	0.029	non-normal distribution
	Inhabitants aged more than 65 years	0.018	non-normal distribution
	Illiterate people	0.000	non-normal distribution
Physical	Households with open sewage	0.131	normal distribution
	Households without garbage collection	0.195	normal distribution
	Households without access to electricity	0.002	non-normal distribution

The significance level (p-value) is 0.05: p-value>0.05 is normal distribution and p-value≤0.05 is non-normal distribution.

Survey created on the Survio platform

1. Specify your level of knowledge about flood vulnerability analysis or mapping.

   ☐ Low ☐ Reasonable ☐ High

2. Do you know the Maquiné river basin, located in the state of Rio Grande do Sul?

   ☐ Yes, I live in Maquiné ☐ Yes, visit periodically

   ☐ Yes, I visited one or few times ☐ No

3. Assign importance points to the ECONOMIC vulnerability indicators so that the total sum is 100.

   Per capita income

   Unemployed people

   People living in rented houses

Househead without income

4. Assign importance points to the SOCIAL vulnerability indicators so that the total sum is 100.

   Population density

   Number of women

   Households with more than 5 people

   Inhabitants aged 0 to 4 years

   Inhabitants aged more than 65 years

   Illiterate people

5. Assign importance points to the PHYSICAL vulnerability indicators so that the total sum is 100.

   Households with open sewage

   Households without garbage collect

   Households without access to electricity

6. Regarding the three dimensions of vulnerability to floods: social, economic and physical. Indicate the importance score among these dimensions.

7. Are there any variable(s) not covered in the above list that you consider essential for the vulnerability analysis?

8. What is your age?

   ☐ Less than 25 years old ☐ Between 26 to 40 years old

   ☒ Between 41 to 65 years old ☐ More than 65 years old

9. Do you work in which of the following sectors?

   ☐ Academic ☐ Governmental

   ☐ Research Institute ☐ Business

10. What is your level of education?

☐ Elementary school ☐ Vocational school ☐ Specialization

☐ High school ☐ Graduate ☐ Master's degree ☐ PhD

11. If you wish to make suggestions for the next questionnaire, use this space.

CHAPTER 5

Conclusions and recommendations

5.1. Conclusions

The present doctoral dissertation aimed to verify sensitivity of flood vulnerability indices through changes in the input parameters. This study was applied to the mountainous Maquiné river basin, southern Brazil, where floods events are frequent.

Regarding the thesis first goal, I identified gaps in the development of flood vulnerability indexes by reviewing 95 articles conducted in 38 different countries, such as: (i) temporally-dynamic aspects were often disregarded; (ii) a few studies focused on indicators that address flood damage and consequences; (iii) sensitivity and uncertainty analyses, applied to the selection of indicators, normalization, weighting, and aggregation process, were often neglected; and (iv) performing results validation was rare.

Based on the gaps identified through the literary review, the effects of use of different normalization, aggregation, and classification methods to construct a flood vulnerability index were investigated. Overall, I found that: (i) the choice of different normalization techniques does not make significant changes in the flood vulnerability outputs; (ii) the choice of aggregation method strongly affects the vulnerability outcomes; and (iii) the presentation of vulnerability results by different classification methods brings changes concerning over- and underestimating the flood vulnerability in some places of the study area.

Another gap was the uncertainty by using different weighting indicators. For this issue, the choice of weights by different people (considering if they knew the study area or specialists in flood vulnerability) had a small effect on flood vulnerability results. Also, the use of equal weights and choice of weights across people did not prove major changes in flood vulnerability outcomes.

However, it is important to note that care must be taken when making generalizations from the results obtained with this study, as they may vary for different areas of study or even for different samples in the same area of study.

Hence, these finds can support water specialists and decision-makers in reducing uncertainty and flood-related disasters. Also, the methods used here can be transferred to other case studies, providing insights regarding the sensitivity of the flood vulnerability indexes.

5.2. Recommendations

Hazards only become disasters if vulnerable people are living in hazard-exposed areas. Therefore, measuring flood vulnerability, as less uncertainties as possible, is fundamental for assessing flood risk and consequently reducing disasters. For this reason, efforts should be taken to conduct studies in order to reduce the uncertainties on vulnerability. It is recommended to perform sensitivity and uncertainty analysis in all steps constructing a flood vulnerability index, such as the choice of indicators, normalization, weighting, aggregation, and classification of results.

Another important step that is rarely performed is the index validation, which typically uses suspected flooding areas to validate vulnerability results. As vulnerability is a broad and multidimensional concept, it is needed that the validation uses indicators that represent the post-flood event conditions, related to the consequences of flood post-events to the people.

Regarding the indicators, many of them are not found in secondary data that can bring specific and relevant information to the study area. Therefore, it is recommended to use questionnaires to obtain them, if possible. In addition, these indicators can help in the validation process of flood vulnerability, bringing information about the consequences of severe events to the local population. On the other hand, it can help to better understand the flood vulnerabilityin rural areas where data availability is scarce, and it allows choosing a more detailed scale of work.

There are a lot of gaps related to the choice of indicators: low data availability; shallow justification of the selected indicators; coping and adaptive capacity indicators were seldom applied; and use the same set of indicators for different scales and contexts, disregarding inherent discrepancies. Future studies must consider risk perception indicators collected by survey or from available data sources (e.g., social media, newspapers, search engines), besides using scale and other specific contexts as justification of its selection.

Most studies focus on pre-event flood vulnerability and consider it as a static phenomenon in space and time. Studies that assess post-flood and future vulnerability scenarios are needed, and research on the inter-indicator relations is fundamental to understand how one indicator affects another.

In general, the study of floods and vulnerability is still a field not well explored, and requires much more scientific effort. Vulnerability is a kind of dynamic characteristic that is still difficult to measure, because it is multidimensional and complex.